# Take-up and Behavioral Responses of Expanding Unemployment Assistance: Evidence from Rideshare and Taxi Drivers*

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**Abstract**

The expansion of unemployment benefits to previously uncovered workers during the Covid-19 pandemic offers a unique opportunity to study safety net coverage and behavioral responses in a population with substantial discretion over hours. We link the universe of administrative trip records from the Taxi and Limousine Commission to an original survey of New York City rideshare and taxi drivers. Roughly 60 percent of drivers received benefits and only 2.5 percent reported a denial, although denials were more common among Black drivers. Two thirds of non applicants cited perceived ineligibility and complexity for not applying. To estimate behavioral responses, we compare recipients and non-recipients around three changes in benefit generosity. Each $100 of weekly benefits reduced the probability of driving by about 2 percentage points and weekly earnings from driving by roughly $45. We find no response to delayed, retroactive lump-sum payments, suggesting the effects reflect work disincentives rather than short-run income effects. Market-wide responses are much smaller, because the added driver supply lowered hourly pay. The exit hazard from not driving spikes after a large cut in benefits, but quickly reverts to its prior level, consistent with benefits delaying the return of a subset of marginal drivers rather than slowing everyone's return. The resulting increase in time not driving is comparable to that of traditional workers, and the implied duration elasticity is small. Our estimates inform future expansions of safety net coverage to gig workers.

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# 1 Introduction

The Covid-19 pandemic caused extraordinary disruptions in labor markets. In response, policymakers enacted an unprecedented expansion of the unemployment insurance (UI) system through the temporary extension of UI assistance to previously uncovered workers, mostly via self-certification of need.[1] Nationwide, nearly as many workers received benefits under this newly expanded program as under traditional UI. This expansion offers a unique opportunity to empirically investigate key questions in labor and public economics: Who took up these new government benefits? Was access effectively targeted? Were there notable gaps in take-up? Additionally, as public insurance was extended to workers with greater discretion over labor supply, to what extent did the new benefits influence work decisions?

To address these questions, we focus on an important subset of workers who became newly eligible for expanded benefits: taxi and rideshare drivers in the "gig" economy. We link an original survey of drivers that captures their UI application, take-up decisions, and experiences with the benefit process to high-frequency administrative trip records collected by New York City's Taxi and Limousine Commission (TLC). This linkage enables us to examine take-up rates, eligibility gaps, and barriers to participation, as well as to analyze behavioral responses using administrative earnings records. While our analysis focuses on New York City, these rideshare and taxi drivers were especially hard-hit by the pandemic and, in many respects, embody the archetypal gig workers that policymakers had in mind when expanding unemployment assistance.

While the literature on unemployment insurance and benefit take-up is extensive, including studies from the Covid era (Ganong et al. 2024; Bell et al. 2024; Holzer et al. 2021), we study a less examined group: nontraditional (gig) workers who received expanded coverage during the pandemic.[2] These workers differ from traditional em-

[1]The program was known as "Pandemic Unemployment Assistance" (PUA). While not technically "insurance," as claimants had not previously paid into the system, PUA was paid out via state UI systems in a similar manner to traditional UI. For convenience, we refer to PUA and UI interchangeably in the text.

[2]The literature on benefit access has also highlighted racial disparities; see Skandalis et al. (2022); Elzayn et al. (2025).

ployees in exercising far greater discretion over their hours and labor force attachment, which raises new empirical questions and policy challenges amid limited direct evidence (Skandalis and Khoury, 2024). While Jackson et al. (2025) examine self-employed and gig workers in annual tax data, we provide original survey evidence on UI participation and leverage high-frequency TLC administrative data. As a result, we are able to adapt empirical methodologies commonly used in the UI literature to measure labor supply responses and provide parameter estimates for gig workers that are directly comparable to those for traditional employees.

We find that expanding UI provided an important safety net during the crisis. Drivers faced a severe shock—earnings declined 75 percent between March and April 2020, and only slowly and partially recovered over the next two years. On average, 62 percent of drivers reported they applied for UI benefits. The main reason why a driver did not receive UI appears to be that they did not apply. Only 2.5 percent reported denials, consistent with New York following a policy of self-certification. Most of those who did not apply did not believe they would be eligible or felt it was too complicated to apply, which suggests possible confusion about eligibility and administrative burden/hassle costs potentially deterred many eligible drivers from applying. We find no differences in application rates by race, but Black drivers report facing higher denial rates. At the same time, compared to UI, the take up of other benefits, such as PPP and SNAP, was substantially lower, suggesting that UI may have been more accessible.

Understanding how drivers' labor supply responded to these benefits is of both theoretical and practical importance for evaluating pandemic-era policies as well as informing the design of optimal UI schemes going forward. A classic result from the optimal UI literature requires weighing the benefits of an expanded safety net against the potential disincentives to labor supply created by increased benefit generosity (Baily, 1978; Gruber, 1997; Chetty, 2006). At the time policymakers were considering the expansions, there was little empirical evidence on how gig workers might respond to such benefits, as much of the literature has focused on traditional workers during periods of economic crises (e.g. Rothstein, 2011; Farber and Valletta, 2015; Chodorow-Reich et

al., 2019; Johnston and Mas, 2018).

One contribution of our paper is to provide empirical evidence on these questions. The key challenge is that simply comparing the labor supply of UI recipients to non-recipients does not yield unbiased estimates of the impact of UI benefits. Differences in earnings between the two groups can arise via two main channels. First, UI recipients may have experienced more severe negative shocks—the very reason they applied for benefits—resulting in lower observed earnings. Second, there may be behavioral responses, where UI recipients reduce work after receiving benefits.

To isolate behavioral effects, our empirical strategy expands on recent literature examining workers' responses to major changes in benefit generosity during this period: the ending of a $600 weekly benefit supplement from August 2020, the introduction of a $300 supplement at the end of that same year, and the ending of the PUA program in September 2021. To account for other supply and demand factors that may vary around these events, our first empirical strategy uses those who reported not receiving UI as a control group. We reweight non-UI recipients to have similar self-reported pandemic exposure as recipients. The key idea underlying this empirical strategy is that non-UI recipients differ only in their actual (or perceived) ineligibility for UI. Using this difference-in-differences design, we find that each $100 increase in benefit generosity reduced the probability of working by 1.7–2.1 percentage points, reduced hours per week by 0.65-0.93, and reduced earnings by $29-$45. In contrast, we find no change in labor supply around two delayed $900 weekly payments that drivers received, after they had made their labor supply decisions. This suggests that the labor supply effects we observe are due to work disincentives associated with UI, rather than an "income effect" from receiving higher income from benefits that week.

Because recipients and non-recipients drive in the same market, our difference-in-differences estimates hold the wage fixed and overstate the market-wide response. Using an interrupted time series on the full TLC data, we find that the aggregate hours response is much smaller than the recipient response (e.g. in response to the end of the $600 supplement, we estimate a macro elasticity of about -0.06 versus -0.39), because

the resulting increase in driver supply lowers the hourly wage and induces other drivers to cut back. As a result, the additional driving does not raise average earnings: in fact, they even fall slightly, consistent with drivers competing for a relatively fixed pool of demand in the period we study.

A key parameter for assessing the social costs of UI benefits is the duration elasticity measuring the percentage response of the duration of non-employment to a percent change in benefits. We measure this in our context as the percent change in weeks not driving in response to a percent change in benefits. While we observe a sudden spike in the exit hazard following reductions in benefit generosity, consistent with the greater discretion gig workers have over their labor supply and the lack of search frictions associated with returning to gig work, only a subset of drivers appear to be highly responsive to benefits, and the exit hazard quickly reverts to the pre-existing rate. While the subset of drivers who are highly responsive have large implied increases in their durations not working, the percent change in benefits is extremely large, and as a result the implied increase in duration is similar to that for traditional employees during this period (Ganong et al., 2024). The patterns we observe are consistent with reductions in work for most drivers being driven by the pandemic shock itself—such as high reservation wages resulting from pandemic risk and low trip demand—rather than benefit-induced disincentives. The small implied duration elasticity suggests the social cost of extending UI to the gig workers we study was relatively modest.

The remainder of this paper is organized as follows: Section 2 provides policy and institutional background, Section 3 describes the administrative data and our survey in detail, Section 4 examines determinants of UI take-up, Section 5 provides causal estimates of the labor supply response, and Section 6 concludes.

# 2 Background and Institutional Context

In the United States, employees receive partial wage replacement when losing their jobs through the unemployment insurance (UI) system, which is financed by an employer

payroll tax. During periods of high unemployment, such as during recessions, the federal government funds additional weeks of benefits. However, about 10 percent of the workforce falls outside the so-called "covered workforce" at any given time—either due to earnings or tenure requirements, or because they are self-employed. As a result, gig workers, as self-employed independent contractors, are excluded from UI coverage. Meanwhile, gig work facilitated by online platforms has expanded rapidly in recent years (Garin et al., 2022), raising concern that more workers are falling outside of the social safety net.

This gap in traditional coverage became urgent as the Covid-19 pandemic hit. New York City, the pandemic's initial major U.S. epicenter, reported its first confirmed case on March 1, 2020; subsequent lockdowns began March 16, 2020, with many restrictions lasting until June 2021 and the formal state of emergency ending only in November 2022.[3] The shock underscored gig workers' vulnerability and prompted the unprecedented expansion of UI benefits to previously uncovered workers via the CARES Act, passed on March 27, 2020. The new, temporary expansion of unemployment assistance was known as "Pandemic Unemployment Assistance" (PUA). While there was initially confusion regarding whether gig workers would qualify, on April 5, a directive from the Department of Labor specifically mentioned rideshare drivers like those we study: "a driver for a ridesharing service who receives an IRS Form 1099 from the ride sharing service... may still qualify for PUA benefits if he or she has been forced to suspend operations as a direct result of the Covid-19 public health emergency, such as if an emergency state or municipal order restricting movement makes continued operations unsustainable" (DOL 2020).

Although the funds for PUA came from the federal government and not from state UI trust funds, state UI offices (in our case, the New York State UI office) delegated the task of managing claims and determining eligibility under the program. While discretion may have varied across states, New York permitted claimants to qualify based on self-certification of Covid-related unemployment (Jackson et al., 2025; United States

[3]A timeline of key events is provided in Appendix Table A.1.

Government Accountability Office, 2022). Our survey provides direct evidence on the application experience; to the extent that eligibility was largely worker-determined, our evidence from this period provides an opportunity to study the effects of UI policies where qualification depends mainly on self-certification.

Regardless of pre-Covid earnings, the PUA program provided a minimum benefit of one-half the state average Weekly Benefit Amount (WBA). Workers could also submit earnings documentation to determine a benefit amount up to the maximum state benefit. In New York, the average WBA amount as of the end of 2019 was $385, and the maximum benefit was $504. Therefore, the minimum and maximum PUA benefits were $193 and $504, respectively. In addition, workers receiving PUA were eligible for federal top-ups under Federal Pandemic Unemployment Compensation (FPUC) and Lost Wages Assistance (LWA). FPUC was first implemented under the March 2020 CARES Act and provided a $600 supplemental payment that ended August 1, 2020. Following the ending of the $600 supplement, LWA provided a $300 supplemental payment for qualifying weeks through September 6, 2020, but these payments were uncertain to claimants in real time. In New York, the announcement that LWA benefits would be paid out was not made until September 10, 2020. The Covid Relief Bill, signed into law December 27, 2020, renewed FPUC at $300 per week. After being extended again under the American Rescue Plan, the $300 supplemental payment was then paid continuously through September 4, 2021, when the PUA program ended.

In addition to federal policy changes, concurrent state policy and legal developments have also shaped UI eligibility for rideshare and delivery workers. In New York State, a July 2020 federal district court decision, *Islam v. Cuomo*, required the New York State Department of Labor to classify rideshare drivers as employees for UI purposes and to obtain wage records from the rideshare companies. Thus, drivers in New York State could technically have applied for and have been eligible for traditional UI rather than PUA after July 2020.

Finally, states implement different policy rules regarding part-time work, which can significantly impact gig workers' receipt of unemployment benefits. In New York, at

the start of the crisis, any day of work regardless of the number of hours reduced UI benefits by 25 percent. These rules were subsequently relaxed. Beginning January 18, 2021, New York permitted part-time work of up to 4 hours per week and/or earnings up to $504 per week without any loss of benefits. On August 16, 2021, the allowable hours threshold was further expanded to 10 hours.

# 3 Data

## 3.1 TLC Administrative Data

One limitation in studying the effect of PUA is the scarcity of administrative data on affected workers. In general, there are few data sources that capture gig work. We draw on one unique source of such data, trip-level data collected by the New York City Taxi and Limousine Commission (TLC). These data are collected according to mandated data sharing relationships the TLC has with the taxi companies and the major rideshare platforms,[4] and cover the universe of trips with pickups in the five boroughs of New York City.[5] The data include passenger fares paid by passengers after passenger incentives, driver pay, tips, the time of request, and the time and geo-stamps of passenger pickups and drop offs. In addition, our data sharing agreement provides additional fields not included in the public use data, including driver identifiers, time stamps for app logins and logouts, and driver bonuses/incentives. Importantly, our data sharing agreement with the TLC allows us to match survey responses to individual drivers. All results are presented in a manner that protects the confidentiality of individual responses.

Using the administrative data, we aggregate driver pay to the week, beginning on a Monday.[6] For our measure of gross pay, we include tips and driver bonus incentives.

[4]These reporting requirements apply to "high-volume for-hire vehicles" (HVFHVs) that dispatch more than 10,000 trips per day. These include Uber, Lyft, Juno and Via.

[5]Thus, the data include pickups in the five boroughs of New York City (but not out-of-town pickups with in-town dropoffs). Only about 5% of in-town pickups have an "out-of-town" drop off.

[6]This also lines up with a UI week in New York State, where a UI week runs Monday through Sunday.

While we see app log ins and log offs for rideshare, we do not observe this for taxi. To construct a comparable measure of hours between rideshare and taxi, we infer "shifts" following Farber (1999): A shift is considered as ending if there is no additional trip made for four hours. Hours are then calculated as the time from the beginning to the end of the shift. We define hourly pay as total weekly driver pay divided by total shift hours.

## 3.2 UI Survey

In order to better understand the impact of Covid and drivers' interactions with the UI system, we surveyed drivers in February 2024. The full text of our survey instrument is included in Appendix D. Our sample frame consisted of drivers active (defined as making at least 1 trip) in each of the four months from November 2019 to February 2020. The main survey distribution was handled by the TLC, who emailed drivers a link to the survey. Drivers were offered $20 as an incentive for completing the survey, which the researchers paid to the drivers following their completion of the survey. We received 1,149 complete responses for approximately a 1.3 percent response rate.

As part of the survey, drivers were asked to provide their TLC driver license number, which we use to match to the administrative data. In the end, we are able to link 77 percent of the respondents back to our administrative data, for a final sample size of 883 responses.[7]

The usual concern of any survey is representativeness of the respondents. We examine representativeness in Appendix Table A.2 by comparing descriptive statistics in the administrative data between the sample frame and our survey respondents. Survey respondents are about 4 years younger and work about 2 hours less per week on average in 2019, but both groups have very similar gross hourly earnings. Respondents were less likely to be taxi drivers and less likely to have exited (defined as having

[7]There are some invalid responses in the TLC driver license field. In addition, a small number of drivers responded with a valid TLC license number but either should not have qualified for the sample frame (likely because the link was shared with them by another driver), or drove for another non-"high-volume" for-hire-vehicle company outside of Uber, Lyft, Juno or Via that was not subject to taxi reporting requirements. We drop these drivers from the present analysis.

no trips in 2023:Q4).[8] To report results that are representative of the survey frame, we construct propensity score weights based on the variables in Table A.2. All our descriptive statistics are reweighted using these weights.

# 4 Determinants of Benefit Take-up

We begin with high-level descriptive statistics from our survey on the receipt of UI benefits. Table 1 provides summary statistics for key survey questions of interest. Column (1) includes all respondents, and Column (2) focuses on a population that reported driving was their primary activity and had gross earnings of at least $20,000.[9] Most drivers in New York City—82 percent—satisfy the Column (2) criteria. On average, 62 percent of respondents reported applying for UI benefits, and 58 percent reported receiving benefits. The rate of applying and receiving benefits is slightly higher, 65 and 60 percent, respectively, in Column (2).[10] The gap between application and receipt is explained by 2.5 percent reporting having benefits denied, and 1.5 percent reporting their claim was still pending at the time of the survey.

Our survey also asked in what month drivers first applied for benefits, and in what months they received benefits. Appendix Figure A.1 examines the timing of initial claims and what months drivers reported receiving payments. Most drivers reported

[8] Another related point is that someone had to be alive to respond to our survey. Jackson et al. (2025) report an excess mortality rate among older drivers of around 0.5% among drivers 50 years or older. This would amount to approximately 162 drivers in our sample frame. Given this number is small (our response rate implies we are missing just 2 driver responses due to deaths), this cannot be the main cause of the lower exit rate among respondents. We suspect drivers who have exited are just more likely to ignore an email from the TLC.

[9] The $20,000 threshold is chosen because this is the amount of earnings that would trigger a 1099-K tax form reporting earnings that may have facilitated benefit application as proof of eligibility.

[10] Given the lag between receipt in 2020 and the time of our survey in 2024, one concern is recall error. Evidence suggests surveys with even shorter lags suffer from underreporting of UI benefits (Meyer et al., 2023; Larrimore et al., 2022). We think this will be less of a concern in our context given we ask multiple questions to elicit UI receipt. We can compare our estimates both to tax data and the CPS ASEC. While not restricting only to passenger drivers, Jackson et al. (2025) report that 76 percent of primarily platform workers across New York state in 2019 received a 1099-G reporting UI receipt in 2020. In the 2021 CPS ASEC, among those living in New York state in the New York city metro area, whose primary industry in 2020 was "Taxi and limousine service" and whose primary occupation last year was "Taxi drivers" or "Motor vehicle operators, all other," 49 percent reported receiving UI in 2020. The comparable rate for primarily wage earners was 17.1 percent.

applying by April 2020. The number receiving benefits peaks in June 2020, with 66 percent of claimants (41 percent of all drivers) reporting receiving benefits in this month. From here, the share reporting receiving benefits falls steadily to about 20 percent by the end of the PUA program.[11] The average number of months drivers reported receiving UI payments was 7.5.[12]

Among those that applied, most reported submitting tax documentation, mainly a 1099 information return. Very few reported submitting quarterly filings providing a quarterly measure of profits (earnings after expenses) rather than gross receipts, which would likely need to be submitted to determine a base benefit amount greater than one-half the state WBA. For this reason, we believe nearly all of the recipients would have received one-half the state WBA as their base UI benefits, plus the additional federal supplemental payments.[13]

The low denial rates are consistent with New York following a policy of self-certification. Given denial rates were so low, this suggests the main reason someone did not receive UI was simply not applying. Among those who did not apply, we asked a follow up question why. The answers to this question were approximately evenly split between "Not needed," "Don't believe I'm eligible," and "Not sure how/too complicated." The latter two responses suggest possible confusion about eligibility and application burden.

As a simple visual test of whether UI non-recipients appear to have had less need for benefits, Figure 1 examines gross earnings (including zeros) from 2019 to 2023, comparing drivers who reported ever receiving UI with those who did not.[14] Both groups followed very similar earnings trajectories prior to Covid, indicating that non-UI recipients and recipients were comparable before the pandemic. In the initial months

[11]Some drivers still report receiving benefits after the end of the PUA program. This could be due to recall error or could be the result of long delays in determinations or payment.

[12]Note: this may not correspond to actual months of claiming if payments from some months were delayed.

[13]In addition, around 10 percent of drivers did report applying for regular UI as opposed to PUA. If they did receive regular UI and were not routed to the PUA program, these drivers may have received a higher WBA.

[14]This refers to gross earnings; driver net pay also reflects expenses. In Appendix B, we discuss how driver expenses evolved during this period.

of the pandemic, even those who did not report receiving UI saw their earnings fall by more than 75 percent and only gradually recover. This is consistent with even non-UI recipients experiencing a severe economic shock that would have made them potentially eligible for the newly expanded benefits during this period. At the same time, UI recipients had lower earnings during the Covid period, which could reflect more severe shocks and/or behavioral responses to receiving UI. While we will disentangle the behavioral response effect in Section 5, the figure clearly demonstrates that all drivers were highly vulnerable to the Covid shock.

We next examine correlates of UI take-up and denial in a regression framework using the following model:

$$UI_i = f(X_1, X_2, X_3) + \epsilon_i \tag{1}$$

where $UI$ is either self-reported UI application (not necessarily receiving UI), denial, or one of the three main reasons for not applying. We consider three classes of predictors. As discussed above, PUA eligibility would have been based on 2019 earnings history, and we include earnings in our model. We also include an indicator for earning at least $20,000, which is the threshold for receiving a 1099 information return that could then be used as proof of eligibility. Since PUA eligibility was determined at the state level, we include state of residence. Having a W-2 job would have resulted in a record in the state UI system and likely led to denial of PUA for driving activities. We therefore include measures of second jobs and whether or not someone had a W-2 job in 2019.

While all drivers faced similar aggregate economic and pandemic conditions, PUA eligibility was in part determined by a driver's own situation. Our second set of predictors capture some determinants of risk and the size of the individual disruption: presence of children (who would have been home due to school closures), self-perceived Covid risk for oneself, and for dependents.

Our final set of predictors include being a taxi driver (as opposed to rideshare driver), and demographic factors of gender and race. Differences we observe by race

or gender can also be thought of as differences in take up by these groups for reasons not otherwise accounted for in our model, including broader "structural" challenges of interacting with the system that may differ by race.

Table 2 reports linear probability models. We demean 2019 earnings and age, and the remaining regressors are indicators (the exception is one minus the share of 2019 income from driving, which is a continuous variable). The constant is therefore the predicted outcome for a reference driver who is white, male, a rideshare (not taxi) driver, a New York resident, has no W-2 job, earned at least $20,000, has dependents, and perceives both themselves and others in the household to be at high risk from Covid, evaluated at the sample mean of age and 2019 earnings. Each coefficient is the difference in the outcome relative to this reference driver.

Our key findings are as follows: Having a W-2 job is strongly and negatively associated with applying: applications fall by 26 percentage points, with most of this explained by drivers reporting elevated levels of "Not needed" (perhaps because UI was obtained through the traditional job). Note this is after controlling for the share of income that came from driving. UI application is not related to earnings directly, but drivers were less likely to apply if they made less than $20,000, which is the threshold for receiving a 1099-K and this may be partly related to having this documentation. Although non-NY residents have a negative point estimate, it is not statistically significant. Note that only about 5 percent of drivers live in another state. Those without dependents and those who did not deem themselves high-risk for Covid were less likely to apply, by around 8 and 9 percentage points, respectively. There is no effect from perceived Covid risk facing others in the household. Taxi and female drivers were significantly more likely to apply, with both these groups being less likely to report the UI was not needed. Female drivers were also less likely to report the application process was "Too complicated." There are no statistically significant differences in application by self-reported race, however Black drivers were significantly more likely to report being denied UI, and Latino/Hispanic drivers and other races were more likely to report they did not apply because the application process was perceived as too complicated.

Our survey also asked about receipt of benefits from the Paycheck Protection Program (PPP), Supplemental Nutrition Assistance Program (SNAP), and rental assistance/eviction relief. Over 1/3 of drivers report receiving one of these, with around 23 percent reporting receiving PPP, 13.5 percent reporting SNAP, and 5 percent reporting rental assistance/eviction relief. Around half of drivers also reported taking on a new earnings opportunity outside driving (37.5 percent reported any delivery work, and 18.1 percent reported earnings from another job outside the gig economy). In Appendix Table A.3 we examine the predictors of other benefit take-up and taking on additional earnings opportunities in delivery or non-gig jobs. In these regressions, we also include an indicator for receiving UI. We find a positive correlation between UI benefit take-up and PPP and SNAP receipt, indicating UI recipients were more likely to receive these other benefits. This could be related to unobservables, such as the nature of shock or the ability to navigate the application process for benefits. Taking on a new job outside of taxi or rideshare is not correlated with being a UI recipient, at least on the extensive margin. Taxi drivers are less likely to report receiving PPP. Unsurprisingly, not having dependents is associated with a lower likelihood of receiving SNAP, while having a lower income share from driving makes it more likely. Lower income shares from driving are also associated with being less likely to start a new job, but this is likely because these drivers had another job already. Female drivers are more likely to receive PPP and SNAP, and also more likely to engage in delivery work. Older drivers are more likely to receive SNAP and less likely to do other work.

Finally, the last column of Table A.3 investigates the relationship between UI receipt and exit from driving work. Our estimates show no statistically significant association between UI receipt and the probability of exit.

# 5 Behavioral Responses to Expanded Benefits

The previous section documented that many New York City drivers applied for and received UI. We next examine behavioral responses to UI: namely, whether or not these

benefits distorted labor supply decisions.

As Figure 1 shows, all drivers were highly vulnerable to the Covid shock: Even for those who did not report receiving UI, earnings fell more than 75 percent in the initial months of the shock and only slowly recovered. However, the figure also makes clear there was a large gap in earnings between UI recipients and non-recipients precisely during the period UI was offered.

Simply comparing the labor supply of UI recipients to non-recipients does not yield unbiased estimates of the impact of UI benefits. This gap could be explained by two (not mutually exclusive) channels. First, UI recipients could have received worse shocks, or had different characteristics, such as health or caregiving responsibilities, that led them to have lower earnings. A second possibility is behavioral responses: UI recipients could have reduced working after receiving UI. To more credibly identify the impact of UI on labor supply, we exploit high-frequency variation around discrete changes in benefit generosity. Following the onset of PUA, there were two major shifts in benefit amounts: the expiration of the $600 weekly supplement on August 1, 2020 and the onset of the $300 supplement after December 27, 2020. Finally, the program itself ended on September 4, 2021. Another relevant event was the payment of Lost Wages Assistance (LWA) in September 2020. The LWA payments differ from the other changes in benefit generosity because these payments were based on retroactive driving behavior, and drivers were generally unaware of these payments when making work decisions. Therefore, LWA payments would have been unlikely to have influenced contemporaneous labor supply decisions, except through an income effect.

We use two complementary research designs, which we lay out in the next subsection. The first is a difference-in-differences design within our survey sample, which identifies the response of UI recipients holding the market wage fixed (a "micro" effect). The second is an interrupted time series using the full TLC administrative data, which captures the total market response, including any feedback through equilibrium wages (a "macro" effect).

## 5.1 Research Design

### 5.1.1 Difference-in-Differences

This design focuses on our survey respondents who reported receiving UI in the window around each event. We construct a comparison group to control for common trends affecting both UI recipients and non-recipients. To do this, we use drivers who reported never receiving UI, exclude those who indicated that UI benefits were "not needed," and reweight this group to match UI recipients on factors that may have been correlated with pandemic shocks—specifically, the presence of dependents under 18 and self-assessed Covid risk within the household. The experiment we have in mind is that non-recipients differ only in their actual (or perceived) ineligibility for UI, and this ineligibility is otherwise unrelated to labor supply. This identification strategy relies on the standard parallel trends assumption: that in the absence of UI, both groups would have experienced similar economic and pandemic-related shocks. We assess the plausibility of this assumption by examining pre-trends in our outcomes in an event-study framework.

We examine outcomes six weeks around our key events using a standard event-study specification:

$$Y_{it} = \sum_{k \in \{-6,\ldots,6\} \setminus \{-1\}} \beta_k \mathbb{1}\{t - t^* = k\} \times UI_i + \alpha_i + \alpha_t + \epsilon_{it} \tag{2}$$

where $Y_{it}$ is an outcome of interest for individual $i$ in period $t$, $t^*$ is the week where one of the major changes to benefits occurred, $UI_i$ is an indicator for reporting receiving UI in the event window, $\alpha_i$ are individual fixed effects, and $\alpha_t$ are time fixed effects identified by our control group. The $\beta_k$ coefficients trace out the differential response of the outcome among UI recipients, compared to non-UI recipients, and are relative to the omitted week prior to the event week.

Because UI recipients and non-recipients drive in the same market, they face the same market wage. When benefits change, recipients respond both to the change in

benefits and to any resulting change in the wage, while non-recipients respond only to the wage. Writing outcomes in log changes, with $\eta_1$ and $\eta_0$ the labor supply elasticities of recipients and non-recipients and $\mu_1$ and $\mu_0$ any other group-specific changes,

$$\mathbb{E}[\Delta \ln L_i \mid UI_i = 1] = \varepsilon^m \, \Delta \ln b + \eta_1 \, \Delta \ln w + \mu_1,$$
$$\mathbb{E}[\Delta \ln L_i \mid UI_i = 0] = \eta_0 \, \Delta \ln w + \mu_0,$$

so that

$$\beta_{DiD} = \varepsilon^m \, \Delta \ln b + (\eta_1 - \eta_0) \, \Delta \ln w + (\mu_1 - \mu_0). \tag{3}$$

Under parallel trends ($\mu_1 = \mu_0$) and equal labor supply elasticities ($\eta_1 = \eta_0$), the difference-in-differences recovers $\varepsilon^m \, \Delta \ln b$: recipients' response to the change in benefits with the wage held fixed, or the "micro" effect. This is the relevant object for the moral-hazard term in the Baily–Chetty formula. Note that our comparison group is itself affected by the policy, through the wage. While this violates the no-interference component of SUTVA, the spillover operates through a wage common to both groups and is therefore differenced out: the difference-in-differences identifies the direct effect, and the change among non-recipients identifies the spillover.[15]

Self-reported receipt may be underreported in surveys (Meyer et al., 2023). Let $\theta$ be the share of reported non-recipients (our comparison group) who in fact received benefits. If misreporting is unrelated to outcomes conditional on true receipt, the difference-in-differences coefficient is attenuated by the factor $1 - \theta$. Under parallel trends and equal labor supply elasticities, our estimates therefore recover $(1 - \theta) \, \varepsilon_m \Delta \ln b$, and are lower bounds in magnitude on the micro effect whenever $\theta > 0$. An upper bound on $\theta$ comes from comparing receipt in tax data to our survey. Jackson et al. (2025) report that 76 percent of primarily platform workers in New York received UI in 2020, compared with 60 percent in our survey. If this gap reflected only underreporting, it would

[15] If recipients newly pushed toward the participation margin by the loss of benefits respond more (less) to the wage than non-recipients, difference-in-differences would understate (overstate) the micro effect.

imply $\theta = (0.76 - 0.60)/(1 - 0.60) \approx 0.4$, and scaling our estimates by $1/(1-\theta)$, or 1.67. We view this as an upper bound: the tax population is not strictly comparable, and our comparison group consists mostly of drivers who report never applying because of complexity or perceived ineligibility. The attenuation is also smaller if underreporters are less aware of their benefits and therefore less responsive to changes in them.

Both elasticities in Equation 3 are uncompensated: each combines income and substitution effects. The micro elasticity $\varepsilon^m$ reflects both the work disincentive of benefits conditioned on not working and any income effect of higher benefits, while the labor supply elasticity $\eta$ nets the substitution effect of a lower wage, which reduces hours, against its income effect, which raises them. The uncompensated responses are the relevant objects for our purposes, since they describe how drivers actually responded to the policy.

We can separately assess the role of income effects using the delayed LWA payments made following the expiration of the $600 supplement, which raised income without any change in the incentive to work. As discussed above, LWA was a program providing a $300 increase in weekly benefit that technically covered the 6 weeks after the $600 reduction in benefits (the payment periods beginning August 3rd, 10th, 17th, 24th, 31st, and September 7th). However, the payment of these benefits was not made contemporaneously and was not announced with certainty in New York State until September 10th. On September 10, the New York State Department of Labor announced the first 3 weeks would be paid Sept 14.[16] On September 18, the New York DOL announced a second round of payments beginning the week of Sept 21.[17] Given the first announcement on September 10th related to benefits for work through August 23, the availability of these benefits could not have affected driver behavior in these weeks. Drivers who were still collecting UI during this period would have received large lump-sum payments of $900 in the weeks of September 14 and September 21.

[16] https://dol.ny.gov/news/nys-department-labor-announces-300-lost-wages-assistance-payments-will-begin-next-week

[17] https://dol.ny.gov/news/nys-department-labor-announces-nearly-19-billion-lost-wages-assistance-paid-new-yorkers-state

Since payment was not contingent on working in the weeks of payment, any behavioral response in the payment week would occur through a pure income effect rather than work disincentives associated with UI.

To examine the impact of LWA payments, we can estimate event studies around the first payments on September 14th. In Table 3, we also estimate a slightly modified version of our parsimonious event study model:

$$Y_{it} = \beta \mathbb{1}\{t \in 9/14/2020, 9/21/2020\} \times UI_i + \alpha_i + \alpha_t + \epsilon_{it} \tag{4}$$

Thus, $\beta$ estimates the labor supply response in the week LWA payments were made.

### 5.1.2 Interrupted time series

Our second design will exploit the full TLC administrative data, not only survey respondents. We estimate an interrupted time series regression around the same events:

$$Y_{it} = \beta \, \mathbb{1}\{t \geq t_0\} + \gamma \, (t - t_0) + \delta \, (t - t_0) \, \mathbb{1}\{t \geq t_0\} + \alpha_i + \varepsilon_{it}, \tag{5}$$

where $\beta$ is the discontinuous change at the event and $\delta$ the change in trend. Because UI status is not observed for these drivers, there is no comparison group. The identifying assumption is that nothing else changed in the window around $t_0$, on either the supply or the demand side, relative to trend. In our default specification, we choose an event window of four weeks before and after each event.

The interrupted time series includes the response of the wage. For total hours,

$$\Delta \ln L = s_1 \, \varepsilon^m \, \Delta \ln b + \eta \, \Delta \ln w, \tag{6}$$

where $s_1$ is UI recipients' share of hours and $\eta$ is the labor supply elasticity as before.[18] The wage term is nonzero because the wage itself responds to benefits: when benefits fall, recipients increase their labor supply, shifting market supply outward and lowering

[18]This assumes a common labor supply response to the wage among recipients and non-recipients. If responses differ, then the response to the wage is the weighted average of responses, $\bar{\eta} = s_1 \, \eta_1 + (1 - s_1) \, \eta_0$.

the equilibrium wage, so that $d \ln w / d \ln b > 0$. We define the macro elasticity as

$$\varepsilon^M \equiv \frac{\Delta \ln L}{\Delta \ln b} = s_1 \, \varepsilon^m + \eta \, \frac{d \ln w}{d \ln b}. \tag{7}$$

The macro elasticity equals the scaled micro elasticity $s_1 \, \varepsilon^m$ only if the wage does not respond. Because $\varepsilon^m < 0$ and $d \ln w / d \ln b > 0$, the wage response offsets part of recipients' response, and the macro elasticity is smaller in magnitude. Two further features of Equation 6 are worth emphasizing. First, the interrupted time series is an intent-to-treat estimate: it pools recipients with non-recipients, whose benefits did not change. Second, simply dividing it by the recipient share does not recover the micro effect, because doing so also scales up the wage term. Simple scaling is appropriate only for outcomes on which the wage had no effect.

## 5.2 Main results: "Micro" effects

Our primary outcomes are indicators for any trips taken, driving passengers for 4 or 10 hours (these correspond to the allowed part-time thresholds set at different points in time),[19] total weekly hours worked, and weekly gross earnings.

Figure 2 examines extensive margin measures of labor supply around each of the three key changes in weekly benefit generosity. Each row of the figure is a different event window. For each window, we consider the likelihood of having any earnings greater than allowed under the part-time threshold prevailing in the post period (0, 4 and 10 hours, respectively). The left panel of Figure 2 presents the raw data in each event window, while the right panel plots the event study coefficients estimated from Equation 2.[20] Alongside the raw data from our respondents reporting UI in the event

[19] While in general there is some ambiguity in how hours should be properly calculated for gig workers, we use time with passengers for the purposes of this analysis. This is sometimes referred to as "P3" or "engaged time" and is the measure of hours typically used for administrative purposes, although it does not correspond to actual hours worked since it does not account for down-time between rides or time on dispatch.

[20] Note that earnings will not be 0 for UI recipients in the pre-period for multiple reasons. First, we only asked about which month a driver received benefits. This could reflect drivers claiming in some weeks and not others, or drivers could work part-time and still be eligible for full or partial benefits. Drivers could also be claiming benefits while claiming not to be working, although our survey is not able to distinguish this. Finally, there could be recall error in when benefits were claimed; if drivers were not actually receiving

window and matched controls, we also compare to the full sample frame. For the $600 ending, the estimation sample looks very similar to the sample frame; for later events, the estimation sample has somewhat lower employment rates. In each panel, we find drivers' likelihood of working jumps following each event, consistent with behavioral responses to UI incentives.

Table 3 summarizes additional outcomes from a more parsimonious specification with a single post coefficient, estimated over four weeks before and after each event.[21] Panel (a) reports the average total response. As shown in the table, average earnings increased by $208 following the expiration of the $600 supplement, decreased by $129 following the onset of the $300 supplement, and increased by $209 following the ending of PUA.

Event study results around the LWA payments are reported in Figure 3 and results from Specification 4 are reported in row (4) of Table 3(a). We find a precisely estimated zero on labor supply from LWA payments. This suggests our findings from changes in UI generosity are not coming from an income effect from receiving more money in the week, but instead reflect the work disincentives that result from UI benefits being conditioned on reduced labor supply.

We have now examined four different events. However, the events were not of equal size in terms of the dollar change in benefits. To more easily make comparisons across events, Table 3 Panel (b) reports estimates per $100 payments, and Panel (c) reports elasticities with respect to benefits,

$$\varepsilon = \frac{\ln(1 + \hat{\beta}/\bar{y}_{-1})}{\ln(193/793)}, \tag{9}$$

benefits, this would bias us toward finding smaller effects.

[21] This specification estimates an average change in the post period:

$$Y_{it} = \beta \mathbb{1}\{t \geq t^*\} \times UI_i + \alpha_i + \alpha_t + \epsilon_{it} \tag{8}$$

In this specification, we drop the week the event occurs, which is often a week of partial treatment and/or when the last payment from the previous weeks' UI claim would still be received. We use the same four-week window for the interrupted time series, so that the two designs are directly comparable. Standard errors are clustered by driver.

where $\bar{y}_{-1}$ is the pre-period mean for UI recipients.[22]

Scaling responses per dollar, we find the effect sizes are fairly consistent across each change associated with benefit generosity. We find that every $100 in benefits reduced the probability of working at all by 1.7 to 2.1 percentage points, reduced the probability of having passengers in the vehicle for at least 4 hours by 1.8 to 2.9 percentage points, and reduced weekly hours by 0.8 to 0.93 hours. In the last column of Table 3, Panel (b), we estimate each additional dollar in UI reduced earnings from driving by 36–45 cents. This is similar in magnitude to Jackson et al. (2025), who estimate a 48-cent reduction in total earnings for every dollar of UI received among 2019 platform workers using variation in generosity across states.

We calculate elasticities for the end of the $600 supplement and the onset of the $300 supplement. Note the ending of the program reduces benefits by 100%, so the elasticity as we measure it would be undefined. The elasticity of any work in response to benefits is similar around both policies, -0.261 and -0.286. The probability of working was higher by the end of the year, which reduces the percent change in the numerator. In general, the other elasticities are larger for the start of the $300 supplement, given the responses are similar but the change in benefits was smaller. The elasticity of hours with respect to benefits was -0.393 and -0.549, and the elasticity of earnings with respect to benefits was -0.461 and -1.30, around each policy, respectively.

## 5.3 Wage Effects and the "Macro" Elasticity

Given the sizable and sudden changes in labor supply around benefit changes, our setting provides a unique opportunity to observe how UI-induced labor supply responses affect an equilibrium wage directly. Figure 4 plots the evolution of raw hourly wages around each event. Drivers receiving and not receiving UI face similar average wages, consistent with a market-level wage, and wages move in the opposite direction of the changes in labor supply.

[22]We report elasticities in log changes because the change in benefits is large. Arc elasticities also depend on whether changes are measured from the world with the supplement or without it, whereas log elasticities are invariant to this choice.

To check the identification assumption that demand was relatively stable around the changes in benefits, we next examine GPS mobility data for New York City (Appendix Figure A.3). Demand appears to evolve smoothly in the four weeks around the end of the $600 supplement, consistent with no contemporaneous shift in demand for trips. However, there is some evidence of demand changes for the other events we study. Mobility, particularly to workplaces, increased in the week the first LWA payments were distributed. Mobility was falling prior to the $300 onset at the end of 2020, which could be due to seasonality (declining activity around the December and New Years holidays) as well as rising Covid cases during this period, before stabilizing around the same time as the start of the $300 onset. When PUA ended, we see large jumps in mobility which could have put some upward pressure on wages. PUA ended at a time when the 2021-22 school year began in New York City, and this likely explains these aggregate dynamics rather than PUA ending for other workers. Therefore, a decline in wages from more drivers entering after PUA ended may have been mitigated by increased demand around this time.

With these caveats in mind, Table 4 examines the ITS estimates for the $600 ending, as well as the end of PUA. Compared to the DiD estimates, the interrupted time series estimates show smaller extensive margin and hours responses for the market as a whole. Around the end of the $600 supplement, the ITS estimate for hours is 1.09 hours, compared to 5.5 in the DiD. Part of the gap reflects the fact that these are ITT estimates, since the full data pool recipients with non-recipients. But most of the gap appears to reflect the response of the wage, which sharply declines in the weeks following the expiration of the $600 benefit and the ending of PUA benefits.

The decline in the wage is large enough that average earnings do not rise despite the increase in hours. They fall by about $49 around the end of the $600 supplement and are essentially unchanged around the end of PUA (Table 4, column 5). Much of the wage decline reflects lower utilization—the ratio of time with passengers to shift hours—rather than lower pay per passenger hour. Around the end of the $600 supplement, utilization falls by 5.2 percentage points (column 7), and its implied elasticity (0.067)

is about three-quarters of the wage elasticity (0.088). This is consistent with additional drivers dividing a roughly fixed pool of rides. The pattern is weaker around the end of PUA: utilization falls by 2.2 percentage points despite a larger wage decline, so a smaller share of that decline reflects utilization, though demand was also rising at that time.

Our finding that the macro response is smaller than the micro response is consistent with evidence from a variety of other contexts (Lalive et al., 2015; Crépon et al., 2013; Marinescu, 2017). In traditional labor markets, the spillover operates through competition for a limited number of jobs; here, it operates directly through the market wage. Our results also contrast with models in which UI raises wages through bargaining and thereby reduces vacancy creation, amplifying employment effects (Hagedorn et al., 2013). In the gig market, labor demand comes from riders rather than from employers posting vacancies, and that demand was roughly fixed in the summer of 2020, so a higher wage induced by UI redistributes a fixed pool of pay rather than reducing the number of jobs.

For optimal UI, Landais et al. (2018) show that the optimal benefit equals the Baily–Chetty level evaluated at the micro elasticity, plus a correction that depends on the gap between the micro and macro elasticities and on labor market slack. The slack relevant here is driver utilization within the ride-hail market. Because additional driver hours are spread over a roughly fixed pool of rides, a benefit cut lowers utilization: after the $600 supplement ends, utilization falls, accounting for most of the decline in the hourly wage, while average earnings do not rise. Conversely, when benefits are more generous, fewer drivers share the same rides, so those who continue working are busier. This would imply a positive correction, and an optimal benefit above the Baily–Chetty level evaluated at the micro elasticity, for this market.

## 5.4 Implied Duration Elasticity and Comparison to the Literature

A key parameter for Baily-Chetty in dynamic models, and the most commonly estimated parameter in the UI literature, is the duration elasticity. This is defined as the percent change in the duration of unemployment or of benefit receipt with respect to a percent change in benefits. In our case, we do not observe moves to jobs outside the TLC data. We instead proceed by measuring the duration of not driving: the number of weeks until a driver reappears in the TLC data.[23]

To estimate the duration elasticity, we focus on the end of the $600 supplement, since we view it as the cleanest experiment, and most straightforward to analyze, given the relatively stable demand conditions and large share of drivers on UI at the time benefits were reduced.[24] This event is a temporary policy: the supplement had a statutory end date of July 31, 2020, although whether it would be renewed remained uncertain. The elasticity we estimate is therefore the response to a known, temporary change in benefits. This is the same object estimated for traditional workers in (Ganong et al., 2024).

We begin with the cohort of drivers in our sample frame who were not driving in the week of April 6, 2020 (83 percent of the frame), define an exit from this state as the first week with any earnings, and define the exit hazard as the share exiting in week $t$ among those who have not yet exited. Two additional data limitations need to be addressed. First, we do not observe exits to non-TLC jobs, and 85 percent of the cohort ever return to driving. Our main estimates condition on eventual return, which is appropriate if drivers who never return leave non-employment on the same schedule as returners, but into jobs we do not observe. Including never-returners and assuming

[23] While the literature also sometimes includes returning to the same job in duration elasticities, this is typically known as a "recall." One important difference in our setting is that the decision to return to the same job is voluntary, and not at the discretion of the employer. For this reason, we see our estimates as more comparable to a traditional duration elasticity than to one including recalls.

[24] Additionally, for "PUA ends," the counterfactual would be the "onset of PUA," moving from a world with benefits to a world without benefits, so the percent change in benefits, the denominator of the elasticity, would be undefined.

their exits are unaffected by the supplement provides a lower bound.[25] Second, the hazard pools recipients with non-recipients, which can be addressed by scaling the excess hazard by the share receiving UI among drivers not working in April 2020 (64 percent).[26] This scaling assumes that the lower wage did not affect non-recipients' return hazard, even if it affected their hours worked.

Figure 5 plots the exit hazard for the April 2020 cohort, for all drivers and for eventual returners. When the $600 supplement ends, the hazard jumps sharply, from about 3 percent per week among eventual returners to about 10 percent, and returns to its pre-period level within about seven weeks. The figure also plots the exit rate from UI to new jobs for workers who began claiming in April 2020 in Ganong et al. (2024). For these predominantly traditional workers, the exit rate roughly doubles, from about 0.9 to 2.0 percent per week, and remains elevated for months. Figure 6 shows the same spike-and-reversion pattern among survey respondents, for whom we observe UI receipt directly.

These shapes distinguish two ways the supplement could have delayed returns to work. Under a "flow" effect, the supplement lowers everyone's weekly return rate while it is paid, so the hazard after it ends remains higher than during the supplement. Under a "stock" effect, the supplement holds back a fixed group of marginal drivers, who return at once when it ends; once they have returned, the hazard reverts. The drivers' hazard, with similar levels before and after the spike, points to a stock effect;[27] whereas traditional workers' persistent increase points to a flow effect.

Expected duration is the area under the survival curve,

$$\mathbb{E}[T] = \sum_{t \geq 0} S(t), \qquad S(t) = \prod_{j=1}^{t} (1 - h_j), \tag{10}$$

[25] If instead never-returners engaged in traditional job search, and their job finding responded to the supplement as in Ganong et al. (2024), the pooled elasticity could be higher than our main estimate, because their spells would be longer.

[26] As a result, underreporting of UI as discussed in Section 5.1.1 also affects the duration elasticity, but in the opposite direction from the micro estimates.

[27] Equal hazards before and after the spike are consistent with no flow effect but do not prove it: dynamic selection, the lower wage, and seasonal conditions all lower the post-period hazard and could mask a modest flow effect.

where $h_j$ is the exit hazard in week $j$ of the spell. We compute survival curves with and without the supplement, holding the hazard at its baseline level $h_0$ after the event window. The effect of the supplement on duration is the area between the two survival curves, $\Delta\mathbb{E}[T] = \sum_t \left[S^{\text{with}}(t) - S^{\text{without}}(t)\right]$. Under a stock effect, the supplement changes *when* marginal drivers return, not *whether* they do, and leaves the exit timing of other drivers unchanged, so $\Delta\mathbb{E}[T]$ = (share delayed) × (average delay). Among eventual returners, scaled by the recipient share, 20.5 percent of recipients are delayed. If they would otherwise have returned at the start of their spells, the average delay is about 15 weeks, and the supplement raised expected duration by 11.9 percent.[28]

For traditional workers, applying the flow mapping of Ganong et al. (2024), in which the supplement lowers the weekly job-finding rate by $\tau = 0.77$ percentage points in each supplement week, to their April cohort reproduces their reported estimate. In that case, fewer workers are delayed (about 10 percent), but each is delayed much longer (about 68 weeks), because when the supplement ends they rejoin a pool that finds jobs only slowly. The resulting increase in duration, 11.5 percent, is similar to our upper-end estimate for drivers.

Dividing by the log change in benefits, $\ln(793/193) = 1.41$, the implied duration elasticity for drivers is 0.08. Using the same log convention, the estimate for traditional workers in Ganong et al. (2024) is about 0.12.[29] The similarity of the duration effects despite the much larger percentage change in benefits for drivers implies a lower elasticity for drivers.

We can also easily compute the static Baily–Chetty statistic, the elasticity of the non-employment rate with respect to benefits. Recipients' share not working fell from 0.77 to 0.67 after the \$600 supplement ended, implying $\ln(0.67/0.77)/\ln(193/793) \approx 0.1$, which lines up closely with the dynamic response for gig workers in this case. Both estimates are driven by the same marginal group of recipients; their similarity in magnitude depends on the front-loaded timing assumption in the duration calculation.

[28] An alternative assumption is they would instead have returned as the city reopened in June and July, the delay is about 6 weeks and the increase is 4.5 percent.

[29] They report 0.06 using percent changes measured from the no-supplement baseline.

## 5.5 Participation With and Without Search Frictions

Why does the exit hazard for drivers spike and quickly revert, while the job-finding rate for traditional workers stays elevated? We interpret the contrast with a stylized participation model, laid out in Appendix C, in which the key difference is whether returning to work requires costly search. In the model, a non-working individual returns to work (or begins searching) when the disutility of working, which has a persistent and a transitory component, falls below a cutoff that decreases in the weekly benefit.

For traditional workers, finding a job requires search effort. A benefit cut therefore raises the effort of workers who are already searching and brings new workers into search. Because search succeeds only gradually, both margins raise the hazard in every subsequent week: a flow effect. For gig drivers, work requires no search, since a driver who logs on receives rides, and working in one week does not commit a driver to the next. The decision is static. A benefit cut raises the cutoff, drivers whose persistent disutility lies between the old and new cutoffs return immediately, and the remaining non-workers lie above the new cutoff, so the hazard reverts to its baseline: a stock effect. The sharpness of the drivers' response thus reflects the absence of search frictions, not greater responsiveness.

The stock-effect logic also pins down the duration elasticity. Because the supplement changes when marginal drivers return, not whether they do, the increase in expected duration equals the share released, $m$, times their average delay, $D$:

$$\varepsilon_D \;=\; \frac{\ln\!\big(1 + mD/E[T^0]\big)}{\ln(b_1/b_0)}, \tag{11}$$

where $E[T^0]$ is expected duration without the supplement and $b_1$ and $b_0$ are benefits with and without it. The elasticity depends on the mass of non-workers near the participation margin and on how long they are delayed. A brief response from a modest share of drivers, set against a very large percent change in benefits, therefore implies a small elasticity.

Calibrating the two versions of the model (Figure C.2) reproduces the shapes in the

data: a spike followed by reversion without search frictions, and a persistent increase with them. The model also implies a one-week release, whereas the data spread it over about three weeks, which may reflect drivers gradually learning that the supplement had ended or the existence of other short-term frictions, such as singing a new vehicle lease.

# 6 Conclusions

Gig economy workers, such as rideshare and taxi drivers, represent a rapidly growing segment of the labor force but have historically been excluded from UI coverage. Policymakers have proposed permanent expansions of traditional UI to include gig economy workers. For instance, Washington State became the first state to put a new policy framework in place, extending traditional UI coverage to Uber and Lyft drivers in 2023. Another proposal for self-employed workers put forward by Abraham et al. (2020) is a means-tested "Job Search Allowance" that would provide benefits similar to PUA, would require job search, and would be funded from general revenues rather than UI taxes.[30] With future crises likely to intensify calls for a more inclusive and equitable UI system, understanding the impacts of such expansions for these new populations is crucial.

To date, most evidence on UI take-up and labor supply responses has focused on traditional employees. Our study helps close this gap by studying workers who exert control over their hours and who needed to self-certify their eligibility for benefits. We find high take-up rates of expanded UI assistance, but also observe confusion about eligibility, concerns over administrative burden, and disparities in benefit access. These

[30] Abraham et al. (2020) also highlight a key issue regarding worker classification: reclassifying gig workers as employees would make them eligible for traditional unemployment insurance. While these classification efforts are ongoing, UI coverage has already been extended to gig workers outside of standard employment contracts. For example, as discussed above, administrative rulings and a federal district court decision enabled New York State to begin treating Uber and Lyft drivers as eligible for regular UI benefits in July 2020. In addition, following a November 2023 settlement, Uber began paying into the state UI trust fund and the state UI office is now expected to receive quarterly earnings records from Uber. Although there has not yet been a public announcement regarding Lyft, administrative UI Appeals Board rulings and the Islam v. Cuomo case indicate that Lyft drivers should also be eligible for UI in New York State.

findings suggest that even when programs are made more accessible, important inequities remain. Our estimates of the behavioral responses to PUA find a subset of drivers are highly responsive to changes in benefit generosity. Interestingly, there was no distortion around LWA payments that were not tied to contemporaneous labor supply, suggesting that unconditional payments may help gig workers mitigate large, aggregate shocks without labor supply distortions. While we find large behavioral responses around changes in benefit generosity, the changes in benefit generosity were also large. Overall, the implied duration elasticity is similar to traditional workers in this period, and wage adjustments offset most of recipients' response in the aggregate.

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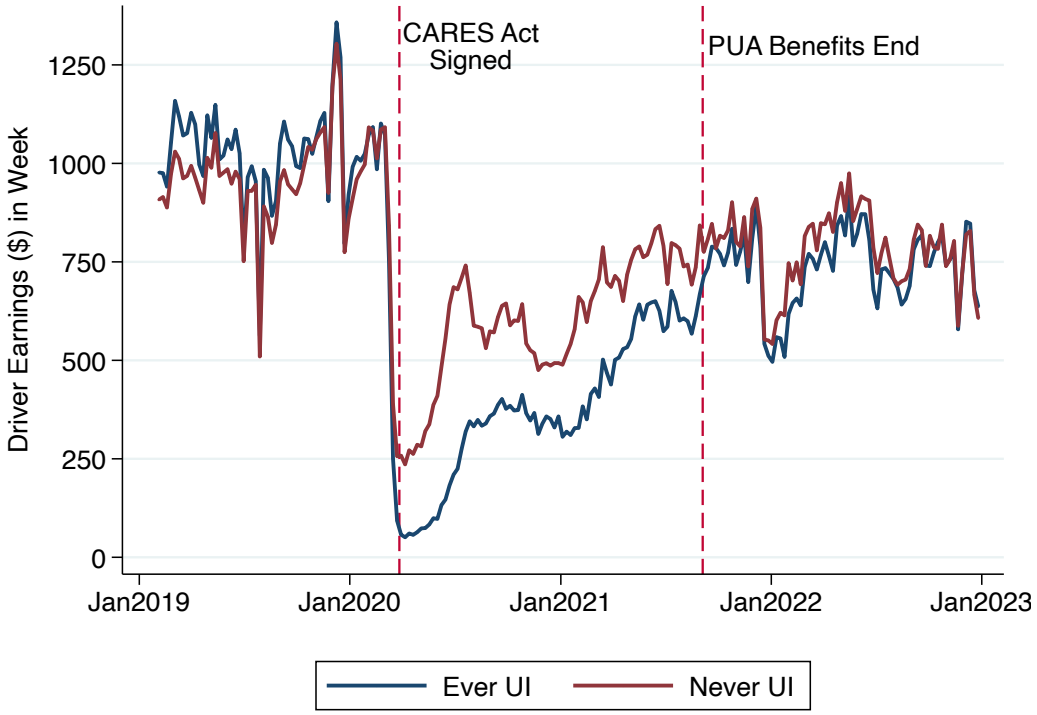
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# Figures

Figure 1: Gross Earnings in Week, By Reported UI Receipt

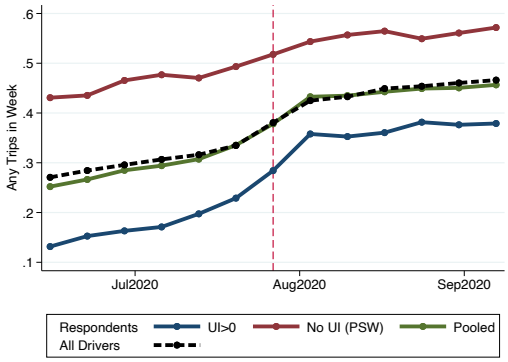



Notes: Figure reports average weekly driver earnings (including those with 0 earnings) in the week. "Ever UI" are survey respondents who reported they received unemployment insurance in at least one month. "Never UI" is the complement.

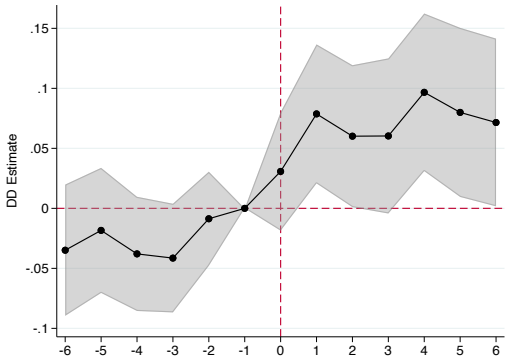
Figure 2: Participation Responses Around Changes in Benefits

$600 Ends

(a) Raw

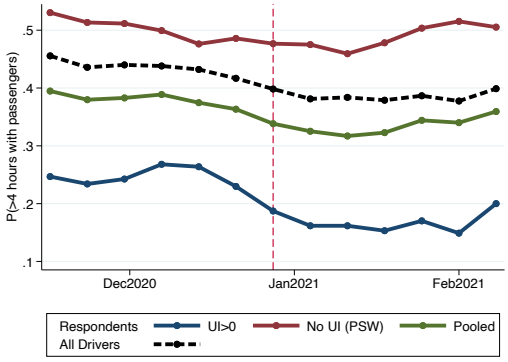



(b) Event Study Estimates

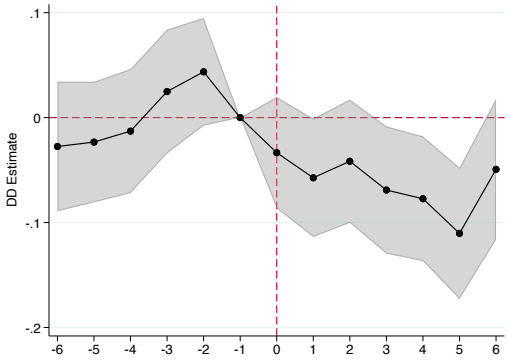



$300 Onset

(c) Raw




(d) Event Study Estimates

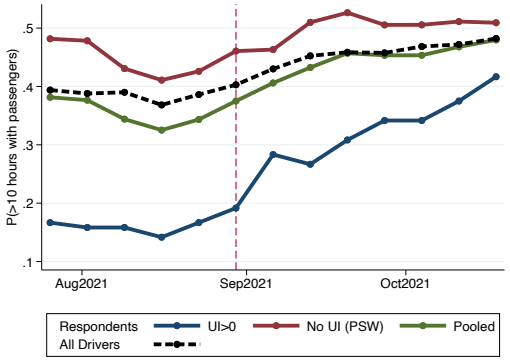



Notes: Outcome changes across panels due to changes in rules around part-time work in New York State. In panels (a)-(b), the outcome is any trips during the week. In panels (c)-(d), the outcome is spending more than 4 hours with passengers. In panels (e)-(f), the outcome is spending more than 10 hours with passengers. Left hand panel reports the raw shares. The navy line reports the share for survey respondents who reported receiving unemployment insurance in the month prior to the event. "No UI" are survey respondents who reported never receiving UI due to complexity or perceived ineligibility, propensity-score reweighted to match the characteristics of UI recipients. The green line is pools both groups. The black solid-line shows the raw average for all drivers in the sample frame (N=87,137). Right hand panel reports the corresponding event study estimates and 95 percent confidence intervals estimated among survey respondents.

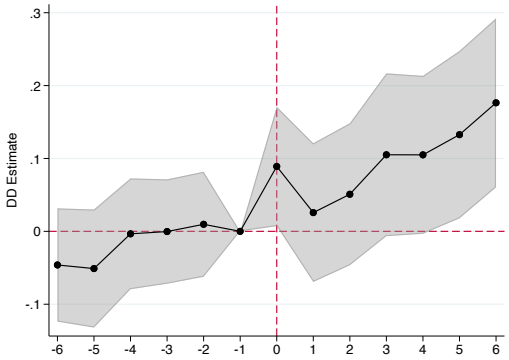
Figure 2: Participation Responses Around Changes in Benefits (Con't)

PUA Ends

(e) Raw



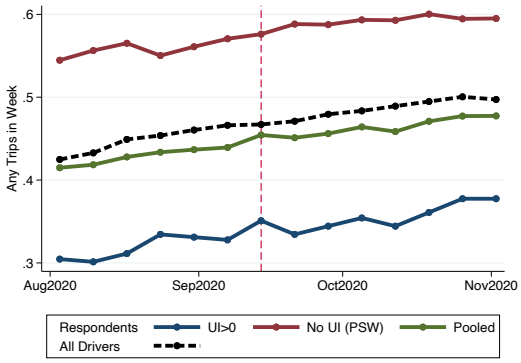

(f) Event Study Estimates



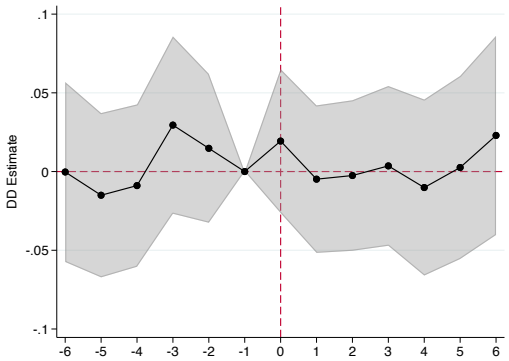

Notes: Outcome changes across panels due to changes in rules around part-time work in New York State. In panels (a)-(b), the outcome is any trips during the week. In panels (c)-(d), the outcome is spending more than 4 hours with passengers. In panels (e)-(f), the outcome is spending more than 10 hours with passengers. Left hand panel reports the raw shares. The navy line reports the share for survey respondents who reported receiving unemployment insurance in the month prior to the event. "No UI" are survey respondents who reported never receiving UI due to complexity or perceived ineligibility, propensity-score reweighted to match the characteristics of UI recipients. The green line is pools both groups. The black solid-line shows the raw average for all drivers in the sample frame (N=87,137). Right hand panel reports the corresponding event study estimates and 95 percent confidence intervals estimated among survey respondents.

Figure 3: Earnings Responses Around First Lost Wages Assistance (LWA) Payment

(a) Raw



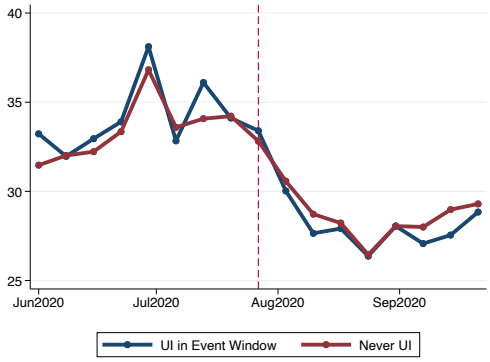

(b) Event Study Estimates



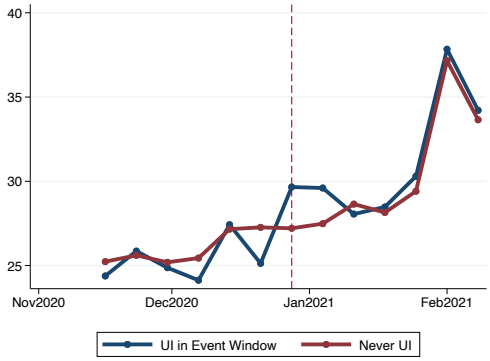

Notes: See notes for figure 2.

Figure 4: Wages Around Changes in Benefit Generosity

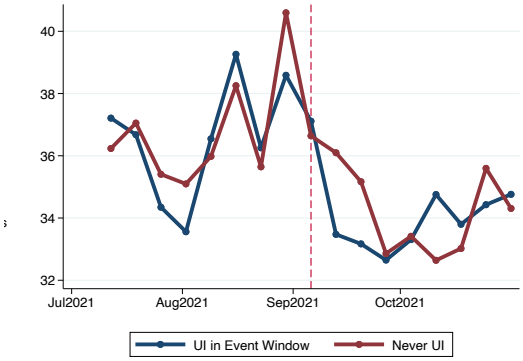
(a) $600 Ends




(b) $300 Onset

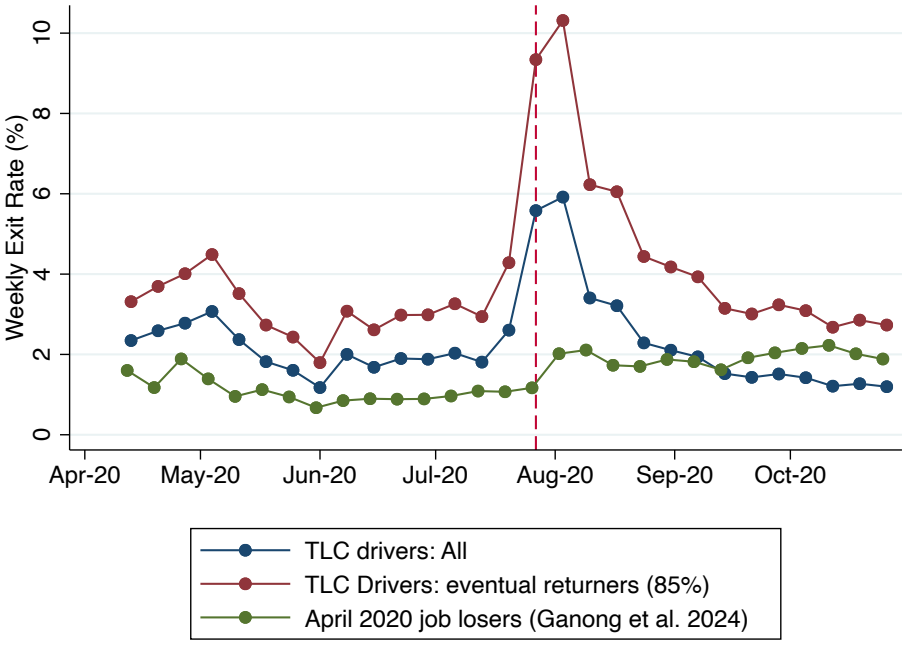



(c) PUA Ends




Notes: Figure examines hourly wages among drivers with any earnings in the period, defined as weekly driver pay divided by shift hours.

Figure 5: Exit Hazard Around End of $600 Supplement-Full Data

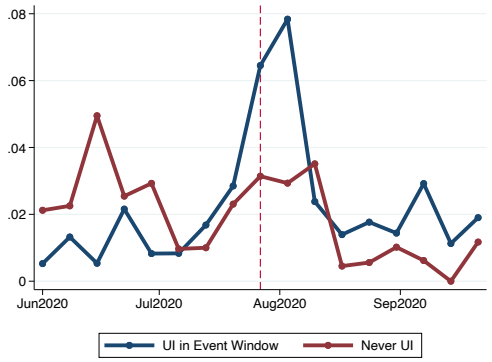



Notes: Figure examines the exit hazard from not working for drivers who stopped working in April 2020. Green line is the exit rate from UI to new jobs for workers who began claiming in April 2020 in Ganong et al. (2024).

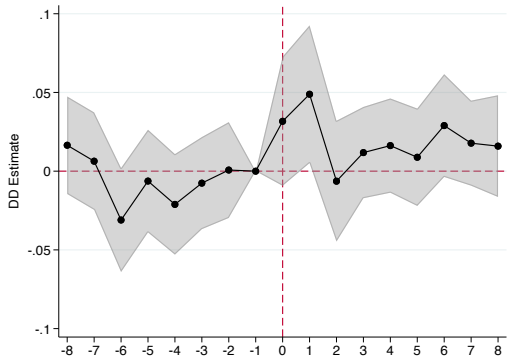
Figure 6: Exit Hazard Around End of $600 Supplement-Respondents

<u>$600 Ends</u>

(a) Raw




(b) Event Study Estimates




Notes: Figure examines the exit hazard from not working for drivers not working in the four weeks preceding the event window.

# Tables

Table 1: Takeup of UI and Other Benefits

| | (1) All | (2) Driving was Primary Job in 2019, Gross Earn>$20,000 |
|---|---|---|
| | % | % |
| **1. Applied for UI** | **62.2** | **64.6** |
| *Outcome:* | | |
| a. Received | 58.2 | 60.2 |
| b. Denied | 2.5 | 2.6 |
| c. Still Pending | 1.5 | 1.8 |
| *Documentation submitted:* | | |
| a. 1099 | 50.1 | 52.2 |
| b. Schedule C/SE | 9.7 | 9.0 |
| c. Receipts/statement from company | 8.1 | 8.2 |
| d. Quarterly filings | 0.8 | 0.5 |
| **2. Did not Apply for UI** | **37.8** | **35.4** |
| a. Not needed | 12.5 | 11.3 |
| b. Don't believe eligible | 12.0 | 10.3 |
| c. Not sure how/too complicated | 12.5 | 13.0 |
| d. Other | 2.8 | 2.4 |
| **3. Receipt of Other Benefits** | **35.7** | **35.1** |
| a. PPP | 23.0 | 22.5 |
| b. SNAP | 13.5 | 13.4 |
| c. Rental assistance/eviction relief | 5.0 | 4.7 |
| **4. Other Work Outside Taxi/Rideshare** | **51.5** | **48.7** |
| a. Delivery-any | 37.5 | 36.8 |
| b. Delivery work provided by TLC | 18.9 | 19.7 |
| c. Delivery for other companies | 21.2 | 20.0 |
| d. Other job outside gig economy | 18.1 | 15.0 |
| N | 883 | 727 |

Notes: Each row reports the percent of all respondents. Column (2) restricted to respondents who reported their primary job was driving and administrative earnings in 2019 are at least $20,000. Respondents could select multiple sources of documentation, reasons why they did not apply for UI, benefits, or other work. Therefore, percents for these decompositions may sum to more than the group totals. "Other" is listing another reason outside of one of the listed reasons above.

Table 2: Predictors of UI Takeup

| | (1) Applied | (2) Denied | (3) Not Needed | (4) Believe Ineligible | (5) Too Complicated |
|---|---|---|---|---|---|
| Constant | 0.744*** | 0.0205 | 0.0912 | 0.151* | 0.0223 |
| | (0.0910) | (0.0207) | (0.0733) | (0.0828) | (0.0484) |
| Has W-2 Job | -0.263*** | -0.00736 | 0.152* | 0.127 | -0.0467 |
| | (0.0809) | (0.0179) | (0.0795) | (0.0824) | (0.0397) |
| 1-Income Share | -0.0316 | -0.00225 | 0.00972 | -0.0650 | 0.0597 |
| | (0.0807) | (0.0173) | (0.0669) | (0.0755) | (0.0428) |
| 2019 Earnings (1000s, demeaned) | -0.000608 | 0.000360 | 0.000607 | -0.00117 | 0.000650 |
| | (0.00100) | (0.000330) | (0.000618) | (0.000743) | (0.000736) |
| Earn<20$k$ | -0.153** | 0.0227 | 0.0791 | -0.00302 | 0.0499 |
| | (0.0706) | (0.0211) | (0.0488) | (0.0542) | (0.0547) |
| Not NY Resident | -0.0924 | 0.0764 | 0.111 | -0.0605 | -0.00385 |
| | (0.0754) | (0.0506) | (0.0691) | (0.0371) | (0.0536) |
| No Dependents | -0.0757** | -0.00568 | 0.0602** | 0.00925 | 0.0156 |
| | (0.0367) | (0.0106) | (0.0259) | (0.0260) | (0.0268) |
| Not Hi Risk-Self | -0.0908** | -0.00239 | 0.0221 | 0.0449 | 0.00210 |
| | (0.0447) | (0.0114) | (0.0276) | (0.0322) | (0.0339) |
| Not Hi Risk-Other | -0.000643 | -0.0100 | 0.0402 | 0.000881 | -0.00955 |
| | (0.0453) | (0.0126) | (0.0268) | (0.0312) | (0.0355) |
| Taxi | 0.197*** | -0.0107 | -0.117*** | -0.0230 | -0.0387 |
| | (0.0512) | (0.0143) | (0.0291) | (0.0344) | (0.0374) |
| Female | 0.318*** | -0.00203 | -0.175*** | -0.0828 | -0.133*** |
| | (0.0645) | (0.0189) | (0.0258) | (0.0523) | (0.0232) |
| Black | -0.00389 | 0.0609* | -0.0204 | 0.0543 | 0.0266 |
| | (0.0737) | (0.0333) | (0.0554) | (0.0550) | (0.0432) |
| Latino/Hispanic | -0.0877 | 0.00506 | -0.0265 | 0.0184 | 0.111** |
| | (0.0578) | (0.0125) | (0.0450) | (0.0390) | (0.0435) |
| Other Race | 0.00729 | 0.0103 | -0.0580 | -0.00459 | 0.0535* |
| | (0.0491) | (0.0116) | (0.0359) | (0.0336) | (0.0309) |
| Age (demeaned) | -0.00140 | -0.000185 | 0.000305 | 0.0000452 | 0.000992 |
| | (0.00173) | (0.000373) | (0.00122) | (0.00117) | (0.00146) |
| $N$ | 883 | 883 | 883 | 883 | 883 |
| $R^2$ | 0.087 | 0.033 | 0.069 | 0.038 | 0.025 |

Notes: Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3: Difference-in-Differences Estimates Around Benefit Changes

| | (1) Earn >0 | (2) P3 >4 | (3) P3 >10 | (4) Shift Hours | (5) Earnings ($) |
|---|---|---|---|---|---|
| **A. Total Estimated Effect** | | | | | |
| 1. $600 expire (Aug. 2020) | 0.102*** | 0.110*** | 0.115*** | 5.50*** | 267.5*** |
| | (0.028) | (0.026) | (0.025) | (1.16) | (42.69) |
| 2. $300 onset (Jan. 2021) | -0.063** | -0.086*** | -0.068** | -2.80** | -134.70*** |
| | (0.024) | (0.023) | (0.024) | (0.96) | (27.87) |
| 3. PUA benefits end (Sept. 2021) | 0.089* | 0.103* | 0.085* | 3.37 | 151.3* |
| | (0.039) | (0.040) | (0.041) | (1.77) | (71.5) |
| 4. LWA Payments (Sept. 2020) | -0.002 | -0.001 | -0.015 | -0.45 | -26.92 |
| | (0.019) | (0.020) | (0.020) | (0.85) | (25.4) |
| **B. Effect per $100** | | | | | |
| 1. $600 expire (Aug. 2020) | -0.017 | -0.018 | -0.019 | -0.92 | -44.58 |
| 2. $300 onset (Jan. 2021) | -0.021 | -0.029 | -0.023 | -0.93 | -44.92 |
| 3. PUA benefits end (Sept. 2021) | -0.017 | -0.021 | -0.017 | -0.65 | -29.35 |
| 4. LWA Payments (Sept. 2020) | -0.000 | -0.000 | -0.002 | -0.05 | -2.99 |
| **C. Elasticity** $\ln(1+\hat{\beta}/\bar{y}_{-1})/\Delta lnb$ | | | | | |
| 1. $600 expire (Aug. 2020) | -0.261 | -0.302 | -0.420 | -0.393 | -0.461 |
| 2. $300 onset (Jan. 2021) | -0.286 | -0.502 | -0.683 | -0.549 | -1.30 |

Notes: Table examines difference-in-differences estimates around the event indicated in the row. Rows (1)-(3) follow specification 8 in the text. Row (4) follows specification 4 in the text. "P3" refers to hours with passengers in the vehicle, not including time spent waiting for the next ride or on dispatch. Standard errors clustered on driver in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

Table 4: Interrupted Time Series Estimates Around Benefit Changes

| | (1) Earn >0 | (2) P3 >4 | (3) P3 >10 | (4) Shift Hours | (5) Earnings ($) | (6) Hourly Wage ($) | (7) Utilization |
|---|---|---|---|---|---|---|---|
| **A. Total Estimated Effect** | | | | | | | |
| 1. $600 expire (Aug. 2020) | 0.072*** | 0.057*** | 0.040*** | 1.09*** | -49.3*** | -4.00*** | -0.052*** |
| | (0.001) | (0.001) | (0.001) | (0.06) | (2.54) | (0.16) | (0.001) |
| 2. PUA benefits end (Sept. 2021) | 0.038*** | 0.038*** | 0.046*** | 1.78*** | -0.759 | -4.45*** | -0.022*** |
| | (0.001) | (0.001) | (0.002) | (0.067) | (9.82) | (0.42) | (0.001) |
| **B. Effect per $100** | | | | | | | |
| 1. $600 expire (Aug. 2020) | -0.012 | -0.009 | -0.007 | -0.18 | 8.2 | 0.666 | 0.009 |
| 2. PUA benefits end (Sept. 2021) | -0.008 | -0.008 | -0.009 | -0.362 | 0.154 | 0.902 | 0.005 |
| **C. Elasticity** $\ln(1+\hat{\beta}/\bar{y}_{-1})/\Delta lnb$ | | | | | | | |
| 1. $600 expire (Aug. 2020) | -0.137 | -0.120 | -0.110 | -0.061 | 0.080 | 0.088 | 0.067 |

Notes: Table reports interrupted time series estimates around the event indicated in the row following specification 5 in the text and uses a bandwidth of 4 weeks. "P3" refers to hours with passengers in the vehicle, not including time spent waiting for the next ride or on dispatch. "Utilization" refers to driver-week ratio of P3 hours to shift hours, among working drivers. Hourly wage and utilization are estimated among drivers who are working; all other columns are unconditional on work. Standard errors clustered on driver in parentheses. * p<0.05, ** p<0.01, *** p<0.001.

# Online Appendix

# A Appendix Figures and Tables

Table A.1: Timeline of Key Dates

| Date | Event |
|---|---|
| March 16, 2020 | Mayor de Blasio orders closure of New York City's bars, restaurants (except for takeout/delivery), nightclubs, and theaters |
| March 22, 2020 | Governor Cuomo "NYS on PAUSE" executive order takes effect, requiring all nonessential businesses to close and implementing strict social distancing measures. |
| March 27, 2020 | CARES Act Signed, creates PUA program and $600 FPUC "top up" to state benefits |
| August 1, 2020 | $600 FPUC benefits end |
| December 27, 2020 | FPUC benefits begin again at lower rate of $300 |
| January 18, 2021 | New York State permits individuals claiming unemployment insurance to work part-time for up to 4 hours per week and/or earn up to $504 before losing benefits. |
| June 24, 2021 | Most Covid-related business and activity restrictions lifted |
| August 16, 2021 | New York State permits individuals claiming unemployment insurance to work part-time for up to 10 hours per week and/or earn up to $504 before losing benefits. |
| Sept 4, 2021 | PUA program ends |
| November 7, 2022 | New York City State of Emergency order lifted |

Table A.2: Survey Representativeness

| | (1) Survey Respondents | (2) Survey Frame | (3) Diff (1)-(2) | (4) Survey Respondents-Reweighted |
|---|---|---|---|---|
| Age | 41.78 | 46.07 | -4.29*** | 46.30 |
| Male | 0.964 | 0.966 | -0.002 | 0.964 |
| Weeks Active | 17.97 | 17.85 | 0.125* | 17.81 |
| Taxi | 0.152 | 0.205 | -0.053*** | 0.210 |
| Weekly Averages, When Active: | | | | |
| Number of Trips | 66.96 | 70.18 | -3.22*** | 70.00 |
| Days Active | 5.35 | 5.44 | -0.091** | 5.43 |
| Hours | 34.85 | 36.72 | -1.988*** | 36.77 |
| Pay | 994.26 | 1,029.33 | -35.06** | 1,027.57 |
| Tips | 63.29 | 80.00 | -16.71*** | 70.88 |
| Hourly Pay | 29.61 | 29.30 | 0.308* | 29.14 |
| Exit (No trips in 2023:Q4) | 0.231 | 0.329 | -0.099*** | 0.343 |
| N | 883 | 87,137 | | 883 |

Notes: Sample frame was drivers with at least 1 trip per month between November 2019 and February 2020. "Survey Respondents-Reweighted" reports propensity-score reweighted means of the respondents using the variables shown in the table.

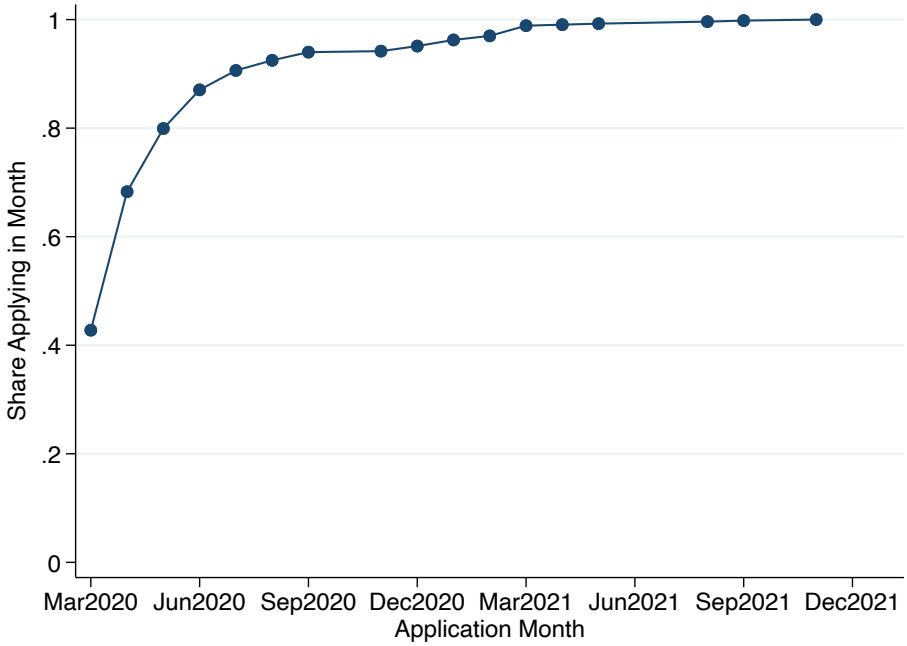
Table A.3: Predictors of Other Benefit Takeup and Additional Earnings Opportunities

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | PPP | SNAP | Rental Assistance | Delivery | Other Non-Gig Job | Exit |
| Constant | 0.216** | 0.0317 | -0.0256 | 0.538*** | 0.539*** | 0.430*** |
| | (0.0925) | (0.0528) | (0.0397) | (0.104) | (0.0961) | (0.101) |
| Received UI | 0.127*** | 0.0699*** | 0.0139 | -0.0472 | -0.00553 | -0.0190 |
| | (0.0310) | (0.0256) | (0.0163) | (0.0381) | (0.0297) | (0.0397) |
| Has W-2 Job | 0.155* | 0.0909 | 0.0193 | -0.133 | 0.116 | 0.0262 |
| | (0.0846) | (0.0560) | (0.0428) | (0.0887) | (0.0919) | (0.0905) |
| 1-Income Share | -0.0572 | 0.139*** | 0.0505 | -0.0397 | -0.354*** | 0.0104 |
| | (0.0832) | (0.0391) | (0.0369) | (0.0904) | (0.0867) | (0.0881) |
| 2019 Earnings (1000s, demeaned) | 0.00218** | -0.00138** | -0.000357 | -0.000122 | -0.000448 | -0.00501*** |
| | (0.000863) | (0.000587) | (0.000358) | (0.00105) | (0.000682) | (0.00101) |
| Earn<20$k$ | -0.0260 | -0.0540 | 0.0200 | 0.0461 | 0.0218 | -0.264*** |
| | (0.0522) | (0.0548) | (0.0332) | (0.0732) | (0.0557) | (0.0767) |
| Not NY Resident | 0.0590 | -0.0548 | 0.0265 | -0.0595 | -0.0197 | 0.0592 |
| | (0.0719) | (0.0480) | (0.0435) | (0.0759) | (0.0521) | (0.0801) |
| No Dependents | 0.0370 | -0.126*** | 0.00294 | -0.106*** | -0.0132 | -0.00241 |
| | (0.0310) | (0.0261) | (0.0159) | (0.0366) | (0.0284) | (0.0389) |
| Not Hi Risk-Self | 0.0182 | 0.00570 | -0.00574 | 0.0185 | -0.0439 | -0.0869* |
| | (0.0361) | (0.0301) | (0.0157) | (0.0419) | (0.0411) | (0.0488) |
| Not Hi Risk-Other | -0.0280 | -0.0168 | -0.0116 | -0.0611 | 0.00422 | 0.0726 |
| | (0.0382) | (0.0310) | (0.0160) | (0.0431) | (0.0398) | (0.0500) |
| Taxi | -0.102** | 0.0143 | 0.00671 | -0.0513 | 0.0703 | 0.0460 |
| | (0.0465) | (0.0411) | (0.0241) | (0.0531) | (0.0443) | (0.0581) |
| Female | 0.193** | 0.155* | 0.0886 | 0.140 | -0.0325 | 0.0474 |
| | (0.0871) | (0.0819) | (0.0628) | (0.0974) | (0.0846) | (0.0967) |
| Black | 0.0662 | -0.0490 | 0.0841** | 0.0950 | 0.0195 | 0.0476 |
| | (0.0712) | (0.0503) | (0.0420) | (0.0736) | (0.0586) | (0.0783) |
| Latino/Hispanic | -0.0129 | 0.0264 | 0.0423 | 0.0197 | 0.0466 | -0.0528 |
| | (0.0511) | (0.0461) | (0.0275) | (0.0587) | (0.0466) | (0.0612) |
| Other Race | -0.0482 | -0.0421 | 0.00843 | -0.0129 | -0.0114 | -0.121** |
| | (0.0439) | (0.0380) | (0.0179) | (0.0474) | (0.0399) | (0.0536) |
| Age (demeaned) | 0.000666 | 0.00267** | -0.0000603 | -0.00358** | -0.00490*** | 0.000166 |
| | (0.00138) | (0.00127) | (0.000625) | (0.00161) | (0.00120) | (0.00189) |
| $N$ | 883 | 883 | 883 | 883 | 883 | 883 |
| $R^2$ | 0.060 | 0.079 | 0.028 | 0.043 | 0.101 | 0.069 |

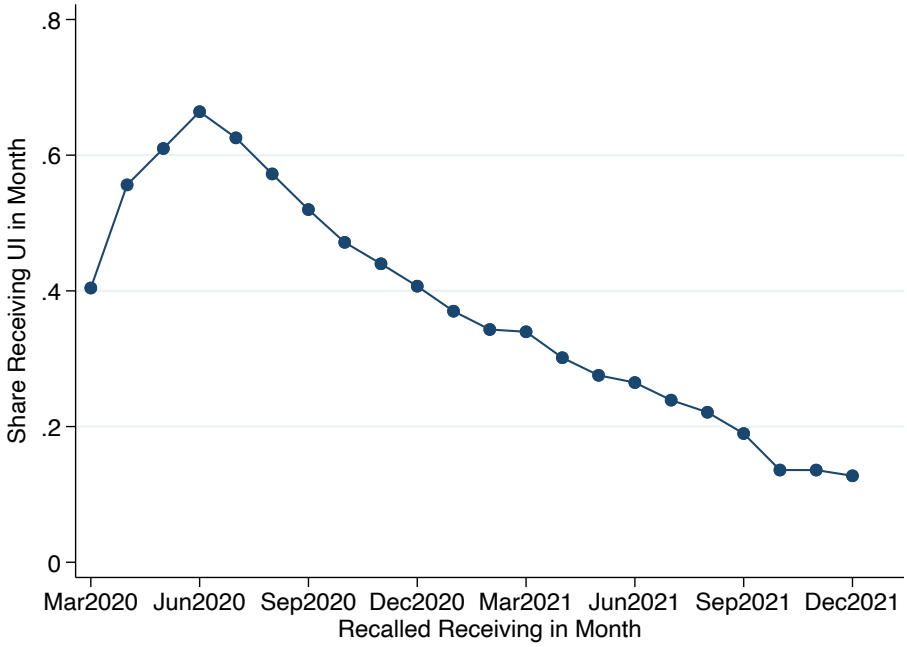
Notes: Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Figure A.1: Initial and Continuing Claims, as Reported in Survey

(a) CDF of Initial Claims

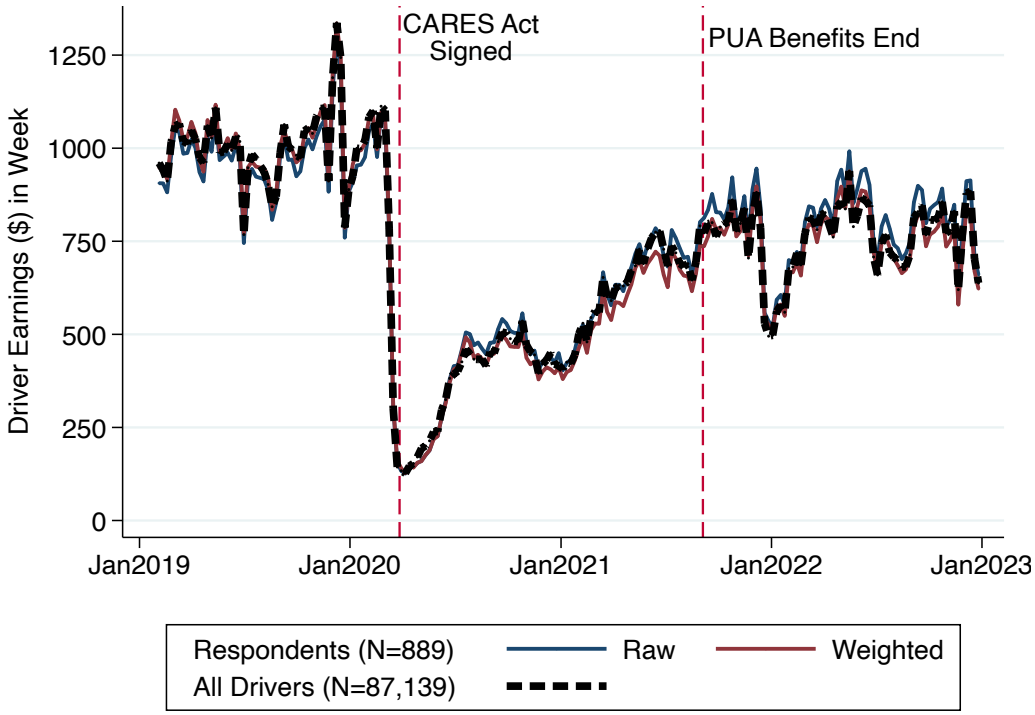



(b) Share of UI Recipients Who Reported Receiving Benefits in Month




Notes: Panel (a) reports the CDF of initial claims in the data by month indicated on the X-axis. Panel (b) reports the share of UI recipients who reported receiving benefits in the month indicated on the X-axis

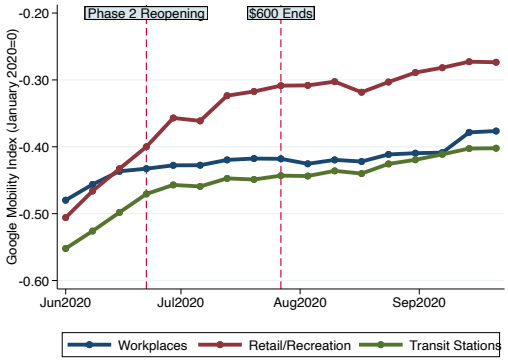
Figure A.2: Gross Earnings in Week,Sample Frame versus Survey Respondents



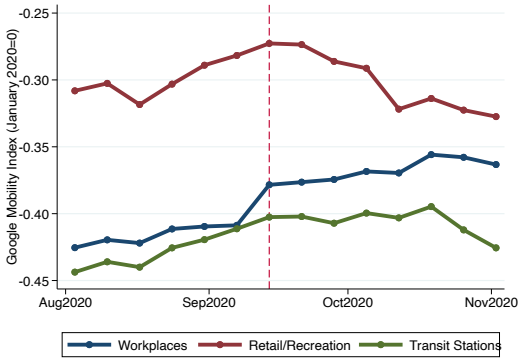

Notes: Figure reports average weekly driver earnings (including those with 0 earnings) in the week, comparing the sample frame of 87,137 drivers (dotted black line), with the 883 drivers in our survey matched to administrative records, both raw (navy line) and reweighted to match the sample frame on observables (maroon line), see text for more details.

Figure A.3: Mobility Around Changes in Benefit Generosity

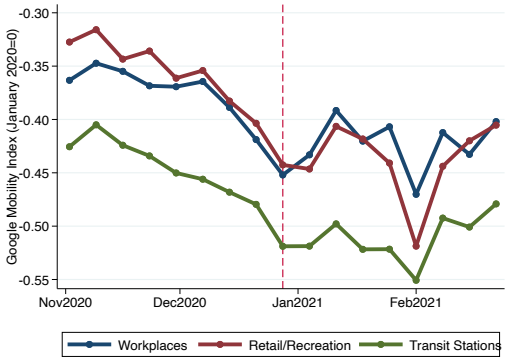
(a) $600 Ends



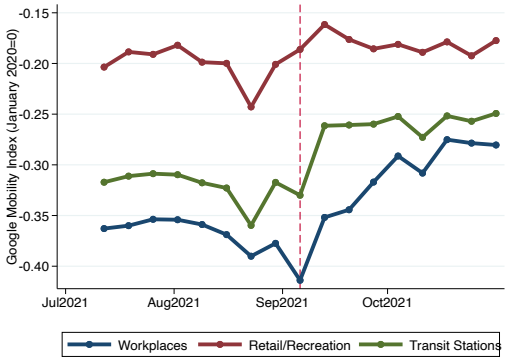

(b) LWA Payments




(c) $300 Onset




(d) PUA Ends




Notes: Figure examines selected Google mobility GPS data for New York City around changes in benefit generosity GPS mobility data indexed to January 3 to February 6, 2020 (Opportunity Insights, 2024).

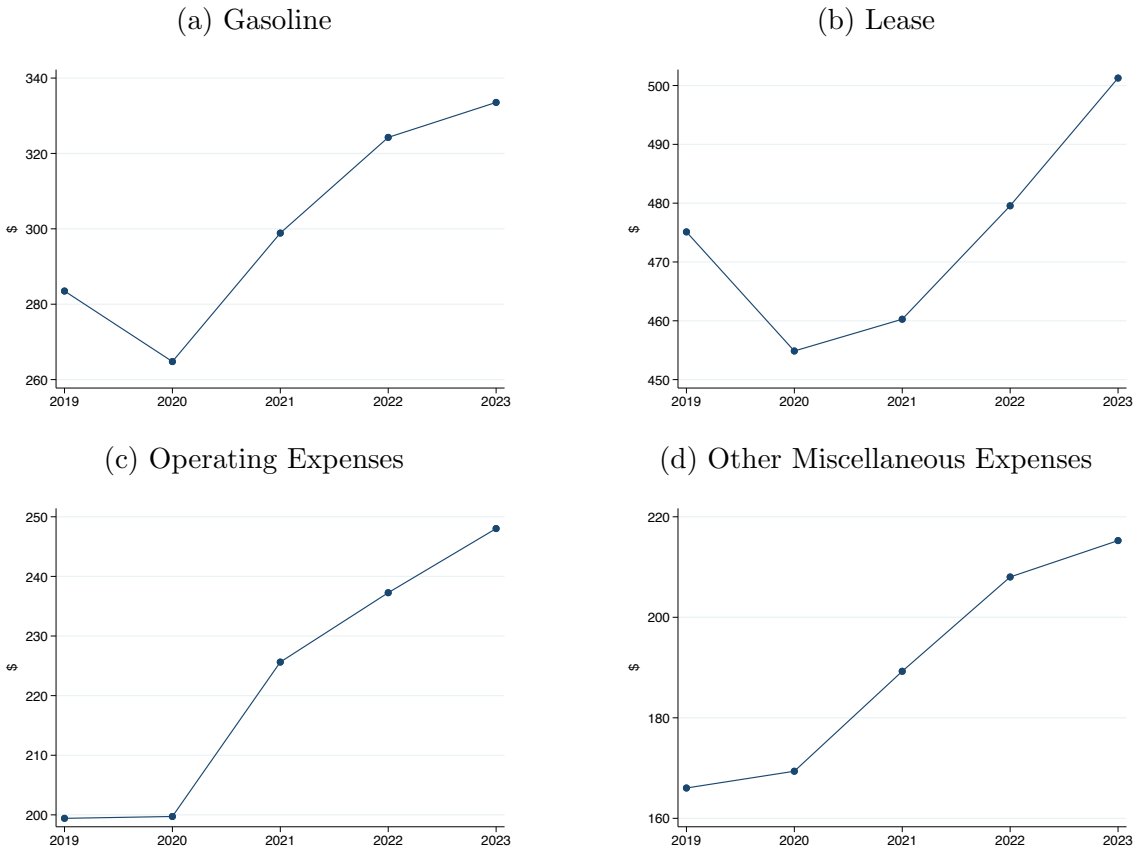
# B Expenses

As shown in Figure 1, drivers saw a dramatic decline in gross earnings during Covid. However, in order to calculate the change in actual take home pay, we need to take into account expenses. While some expenses, like gasoline, are variable and therefore scale with work, other expenses like car payments/leases are often contracted in advance and may be more difficult to adjust. Gas prices also fluctuated during this time, falling in the first year of Covid, before rising back to pre-Covid levels by January 2021, and rising throughout 2021. In addition, drivers may have incurred additional expenses related to acquiring Personal Protective Equipment (PPE) and extra cleaning costs related to operating during the pandemic.

Our survey asked questions about average weekly expenses and also about how drivers were able to adjust their leases. Figure B.1 examines the time series of responses. Reported gasoline expenses fell modestly in 2020, before rising in other years. Lease costs appear to have fallen modestly for 2020 and 2021. Among drivers reporting lease costs, only 33 percent reported they were able to forgo or defer some payments after March 2020. Operating expenses and miscellaneous expenses were relatively flat across 2019 and 2020, before rising from 2021 onward. In addition, the median driver reported spending $300 on additional precautions, with some drivers reporting spending thousands.

Overall, reported weekly driver expenses were relatively stable between 2019 and 2020 and have risen since 2021.

Figure B.1: Reported Weekly Expenses




Notes: Figure examines drivers' reports of typical weekly expenses.

# C A Simple Model of Participation With and Without Search Frictions

This appendix presents the model summarized in Section 5.5. The model delivers three predictions: (1) with costly search, a benefit cut raises the exit hazard in every subsequent week (a flow effect); (2) without search, a cut releases a stock of marginal non-workers who return at once, after which the hazard reverts to baseline (a stock effect); and (3) in the stock case, the duration elasticity is governed by the mass of non-workers near the participation margin, not by how responsive each individual is. We view the model as a framework for interpreting the patterns in the data rather than as a test of them.

## C.1 Setup

Time is discrete and measured in weeks. A non-working individual receives a weekly benefit $b$; a working individual earns a wage $w$, which we take as given. Flow utility $u(\cdot)$ is increasing and concave. The disutility of working is

$$\varphi_{it} = \underbrace{\varphi_i}_{\text{persistent}} + \underbrace{\nu_{it}}_{\text{transitory}}, \tag{12}$$

where $\varphi_i$ captures stable factors such as health risk or caregiving responsibilities, and $\nu_{it}$ captures week-to-week shocks. The weekly exit hazard from non-employment equals optimal search effort. For group $g \in \{T, G\}$ (traditional workers and gig drivers),

$$h_{it} = \begin{cases} 0 & \text{if } \varphi_{it} > \varphi_g^*(b) \quad \text{(not searching)}, \\ s_g(b) \leq 1 & \text{otherwise}, \end{cases} \tag{13}$$

where $\varphi_g^*(b)$ is a participation cutoff that is decreasing in $b$: more generous benefits make fewer individuals willing to work. The two groups differ in how the cutoff is determined and in search effort $s_g(b)$.

## C.2 Traditional Workers: Search With Frictions

A traditional worker who searches with effort $s \in [0, 1]$ incurs a cost $\psi(s) + k$, with $\psi' > 0$, $\psi'' > 0$, and a fixed cost of searching $k \geq 0$, and finds a lasting job with probability $s$. With discount factor $\beta$, the values of unemployment while searching and of employment are

$$V_U = u(b) - \psi(s) - k + \beta \left[ s\, V_E(\varphi_i) + (1 - s)\, V_U \right], \tag{14}$$

$$V_E(\varphi_i) = \frac{u(w) - \varphi_i}{1 - \beta}. \tag{15}$$

Optimal search effort satisfies $\psi'(s) = \beta \left[ V_E(\varphi_i) - V_U \right]$. Because the value of unemployment is increasing in $b$, search effort falls with benefits, $s'(b) < 0$. The worker searches at all only if $V_U$ exceeds the value of not searching this week and continuing to collect $b$; the fixed cost $k$ makes this an extensive margin, which defines the cutoff $\varphi_T^*(b)$.

A benefit reduction therefore acts on both margins. Workers already searching raise their effort, and workers pushed across the cutoff begin searching. Because $s < 1$, workers who newly begin searching find jobs only gradually, at the same rate as other searchers. Both margins therefore raise the hazard persistently in every subsequent week, rather than producing a spike: a flow effect (prediction 1).

## C.3 Gig Drivers: Participation Without Search Frictions

For gig drivers, work is week to week and requires no search: a driver who logs on receives rides. We therefore set $s = 1$. Because working in one week does not commit a driver to future work, the decision is static, and a driver works if

$$u(w) - \varphi_{it} \;\geq\; u(b) \quad \Longleftrightarrow \quad \varphi_{it} \;\leq\; \varphi_G^*(b) \;=\; u(w) - u(b). \tag{16}$$

A benefit reduction from $b_1$ to $b_0 < b_1$ raises the cutoff from $\varphi_G^*(b_1)$ to $\varphi_G^*(b_0)$, a shift of $u(b_1) - u(b_0)$. Non-workers whose persistent disutility lies between the two cutoffs return immediately. Once they have returned, the remaining non-workers lie above the new cutoff, and the hazard reverts to its baseline $p$, which is generated by the transitory shocks $\nu_{it}$.[31] The sharpness of the drivers' response therefore reflects the absence of search frictions, not greater responsiveness (prediction 2).

## C.4 Implied Duration Elasticity

The stock-effect logic links the model to the duration calculation in Section 5.4. Let $F$ denote the distribution of persistent disutility $\varphi_i$ among non-workers just before the cut, and let $m$ be the marginal share released:

$$m \;=\; F(u(w) - u(b_0)) - F(u(w) - u(b_1)) \;\approx\; f(\varphi_G^*(b_1))\,[u(b_1) - u(b_0)]\,, \tag{17}$$

where $f$ is the density of $F$ and the approximation holds for small cuts. Under a stock effect, the supplement changes when marginal drivers return, not whether they do, so $\Delta E[T] = m \times D$, where $D$ is the average delay. The implied duration elasticity is then

$$\varepsilon_D \;=\; \frac{\ln\!\big(1 + mD/E[T^0]\big)}{\ln(b_1/b_0)}, \tag{18}$$

where $E[T^0]$ is expected duration without the supplement. Equation (18) makes prediction (iii) explicit: the elasticity depends on the mass of non-workers near the margin ($m$) and on how long they are delayed ($D$), not on how responsive each driver is. A brief, sharp response from a modest share of drivers, set against a very large percent change in benefits, therefore implies a small elasticity. For traditional workers, by contrast, the flow effect lowers the weekly job-finding rate in every supplement week, so fewer workers are delayed but each is delayed much longer (Section 5.4).

[31] A higher cutoff also makes returns driven by transitory shocks more frequent. The reversion of the hazard to its pre-period level in the data indicates that this channel is small.

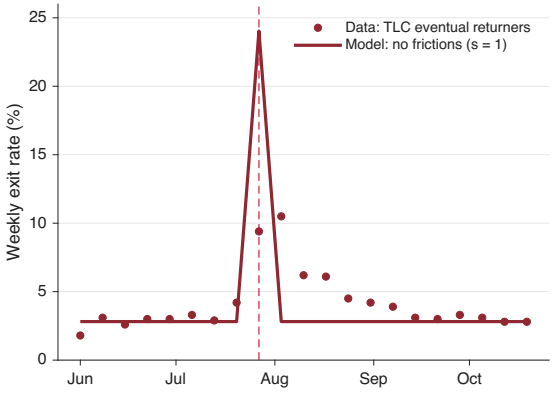
## C.5 Calibration

Figure C.2 calibrates the two versions of the model. For gig drivers (panel a), we set the baseline hazard $p$ to the average exit hazard of eventual returners from June to mid-July 2020, about 2.8 percent per week, and impose $s = 1$. We set the marginal share $m$ so that releasing marginal drivers in the first week without the supplement reproduces the total excess exits observed from late July through mid-September, equal to 13.4 percent of the cohort, or 22 percent of eventual returners not yet working at the event. For traditional workers (panel b), we set the exit rate before and after the supplement ends equal to the average exit rate to new jobs in each period for the April 2020 cohort of Ganong et al. (2024). The exit rate roughly doubles, from about 1.0 to 1.9 percent per week, and remains elevated, consistent with a flow effect.

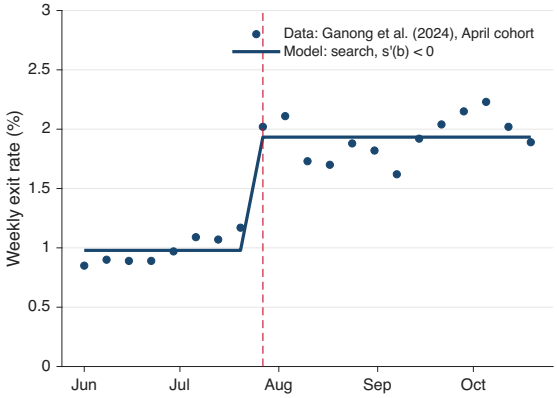
The model implies the spike is released in one-week, whereas the data spread the release over about three weeks. A natural explanation, beyond the scope of the model, is that expectations adjusted gradually: some drivers may not have realized immediately that the supplement had ended, or that it would not be renewed, and returned as they updated.

Figure C.2: Calibrated Model: Participation With and Without Search Frictions

(a) Gig drivers: no search frictions




(b) Traditional UI recipients: search frictions




Notes: Weeks are plotted by their start date; the dashed line marks the first week without the $600 supplement, the week beginning July 27, 2020 (TLC weeks run Monday–Sunday, following New York's UI week). The weeks in Ganong et al. (2024) begin on Sundays, and their first week after the supplement expired begins August 2; we shift their series by six days so that this week aligns with the TLC week beginning July 27. Panel (a) calibrates the participation model with no search frictions ($s = 1$) to the weekly exit hazard of eventual returners in the April 2020 cohort of TLC drivers. The baseline hazard $p$ is the June to mid-July average. Marginal drivers are released in the first week without the supplement, with the marginal share set so that this one-week release reproduces the total excess exits observed from late July through mid-September. Panel (b) fits the search model to the exit rate from UI to new jobs for the April 2020 cohort in Ganong et al. (2024), with search effort equal to the average exit rate before and after the supplement ends.

# D Survey Instrument

# Impacts of COVID on Rideshare Drivers

Start of Block: Consent

info_browser Click to write the question text
Browser (1)
Version (2)
Operating System (3)
Screen Resolution (4)
Flash Version (5)
Java Support (6)
User Agent (7)

JS

clickthrough The survey should automatically load. If not, click “continue to survey” below

Page Break

JS

Header Covid deeply affected New York City's taxi and app-based drivers. To better understand how drivers were affected, researchers from The University of Chicago and The New School are asking you to complete the following survey. TLC is not the party administering the survey. It should take about 15-20 minutes. In return for completing the survey, you will receive **$20 via an Amazon gift card.** Your responses are voluntary and will be confidential. All responses will be compiled together and analysed as a group

- ○ I agree to participate in the research. (1)
- ○ I do NOT agree to participate in the research. If you select this box, you will be taken to a screen that exits you from the survey (2)

Consent **Description**: The Covid crisis has profoundly impacted New York City's transportation sector, including taxi and app-based drivers. In order to better understand how drivers have been affected, we are requesting feedback from drivers like yourself. Participation should take about 15-20 minutes of your time. Your participation is voluntary. **Incentives**: In return for completing the survey, you will receive $10 via an Amazon gift card delivered to an email of your choice within 24 hours of completing the survey **Risks and Benefits:** Your participation in this study does not involve any risk to you beyond that of everyday life. Your participation will help policy makers create better programs for drivers and help deepen our understanding of your unique working arrangement. **Confidentiality**: Your responses will be kept strictly confidential so your answers and driving activity will remain anonymous. All responses will be compiled together and analyzed as a group by academic researchers. The TLC will not have access to your responses and will not maintain a record of your responses. · If you decide to withdraw, data collected up until the point of withdrawal may still be included in analysis. · Identifiable data will never be shared outside the research team. · Some de-identified information from this study may be used for future research studies or shared with other researchers for future research without your additional informed consent. **Contacts & Questions**: If you have questions or concerns about the study or payment issues with the survey incentive, you can contact the researchers at Dmitri Koustas at dkoustas@uchicago.edu or James Parrott at parrottj@newschool.edu. If you have any questions about your rights as a participant in this research, feel you have been harmed, or wish to discuss other study-related concerns with someone who is not part of the research team, you can contact the University of Chicago Social & Behavioral Sciences Institutional Review Board (IRB) Office by phone at (773) 702-2915, or by email at sbs-irb@uchicago.edu. Consent: Participation is voluntary. Refusal to participate or withdrawing from the research will involve no penalty or loss of benefits to which you might otherwise be entitled. By completing this survey, you are consenting to participate in this study.By clicking "Agree" below, you confirm that you have read the consent form, are at least 18 years old, and agree to participate in the research. Please print or save a copy of this page for your records.

End of Block: Consent

Start of Block: Intro block



tlc_num What is your New York City TLC driver's license number?

_____

Page Break

driver_years Have you been an active driver at any point in the below years? Please choose the year and driving service you operated.

| | 2019 (1) | 2020 (2) | 2021 (3) | 2022 (6) | 2023 (4) |
|---|---|---|---|---|---|
| High-Frequency Vehicle (FHV). such as Uber/Lyft/Juno or Via (12) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Black car (13) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Yellow taxicab (14) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Green taxicab (15) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Luxury limousine (16) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Livery (17) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Other (Please indicate below) (18) | ☐ | ☐ | ☐ | ☐ | ☐ |

Page Break

*Display This Question:*

*If Have you been an active driver at any point in the below years? Please choose the year and drivin... = Other (Please indicate below) [ 2019 ]*

*Or Have you been an active driver at any point in the below years? Please choose the year and drivin... = Other (Please indicate below) [ 2020 ]*

*Or Have you been an active driver at any point in the below years? Please choose the year and drivin... = Other (Please indicate below) [ 2021 ]*

*Or Have you been an active driver at any point in the below years? Please choose the year and drivin... = Other (Please indicate below) [ 2022 ]*

*Or Have you been an active driver at any point in the below years? Please choose the year and drivin... = Other (Please indicate below) [ 2023 ]*

other_service What other service have you driven for?

_____

*Display This Question:*

*If Have you been an active driver at any point in the below years? Please choose the year and drivin... [ 2020] (Count) = 0*

*Or Have you been an active driver at any point in the below years? Please choose the year and drivin... [ 2021] (Count) = 0*

*Or Have you been an active driver at any point in the below years? Please choose the year and drivin... [ 2022] (Count) = 0*

*Or Have you been an active driver at any point in the below years? Please choose the year and drivin... [ 2023] (Count) = 0*

why_leave You indicated that you stopped driving between 2020 - 2023. What were the main reasons? (Select all that apply)

- [ ] Low ride volume (1)
- [ ] Low pay (2)
- [ ] Better job opportunities outside of driving (3)
- [ ] High driving costs (e.g. gas, insurance) (4)
- [ ] Account deactivated or fired (5)
- [ ] Health Concerns from Covid-19 (6)
- [ ] Other (7) _____

*Display This Question:*

*If Have you been an active driver at any point in the below years? Please choose the year and drivin... != 2019*

*And Have you been an active driver at any point in the below years? Please choose the year and drivin... != 2020*

*And Have you been an active driver at any point in the below years? Please choose the year and drivin... != 2021*

*And Have you been an active driver at any point in the below years? Please choose the year and drivin... != 2022*

*And Have you been an active driver at any point in the below years? Please choose the year and drivin... != 2023*

never_driven_check You indicated you were NOT an FHV or taxi driver between 2019 and 2023. Is this correct?

- ○ I was NOT an active driver in this time period. (1)
- ○ I was an ACTIVE DRIVER in 2019. Restart Survey. (2)

Page Break

*Display This Question:*

*If You indicated you were NOT an FHV or taxi driver between 2019 and 2023. Is this correct? = I was NOT an active driver in this time period.*

Never_Driven_Msg Thank you. Unfortunately, you are not eligible to complete the survey at this time.

**End of Block: Intro block**

**Start of Block: Earnings and hours worked**

Weekly_Hours_Header The following questions ask about your HOURS worked as a driver PER WEEK (hours include time with passengers OR time waiting for a passenger).

Page Break

*Display This Question:*

*If Have you been an active driver at any point in the below years? Please choose the year and drivin... = 2023*

Typ_Hours What are your current TYPICAL HOURS worked in a WEEK as an FHV or taxi driver? If you worked more than 100 hours, please select 100.

| | 0 10 20 30 40 50 60 70 80 90 100 |
|---|---|
| 1 () |  |

Page Break

*Display This Question:*

*If Have you been an active driver at any point in the below years? Please choose the year and drivin... != 2023*

typ_hours_former_dri Thinking back to your last time driving as an FHV or taxi driver, what do you feel were your TYPICAL HOURS driven per WEEK? If you worked more than 100 hours, please select 100.

| | 0 10 20 30 40 50 60 70 80 90 100 |
|---|---|
| 1 () |  |

Page Break

Weekly_Pay_Header The following questions ask about your WEEKLY PAY.

Page Break

*Display This Question:*

*If Have you been an active driver at any point in the below years? Please choose the year and drivin... = 2023*

Typ_Pay What is your current TYPICAL pre-tax pay in a WEEK as an FHV or taxi driver? If you earned more than $3000, please select $3000.

| | 0 500 1000 1500 2000 2500 3000 |
|---|---|
| 1 () |  |

Page Break

*Display This Question:*

*If Have you been an active driver at any point in the below years? Please choose the year and drivin... != 2023*

typ_pay_forme Thinking back to your last time driving, what was your TYPICAL pre-tax pay per WEEK as an FHV or taxi driver? If you earned more than $3000, please select $3000.

| | 0 500 1000 1500 2000 2500 3000 |
|---|---|
| 1 () |  |

End of Block: Earnings and hours worked

Start of Block: Number of jobs to gauge eligibility

only_job Since 2019, was driving for a taxi or FHV company or companies your only job, or did you do other work too?

- Only job (1)
- Had other work too (2)

*Display This Question:*

*If Since 2019, was driving for a taxi or FHV company or companies your only job, or did you do other... = Had other work too*

other_self_emp Was this other work another include a form of self-employment?

- Yes (1)
- No (2)

Page Break

*Display This Question:*

*If Since 2019, was driving for a taxi or FHV company or companies your only job, or did you do other... = Had other work too*

pctincomdriving What percentage of your **total annual income** came from earnings as a TLC driver?

| | 0 10 20 30 40 50 60 70 80 90 100 |
|---|---|
| In 2019 () | |
| In 2020 () | |
| In 2021 () | |
| In 2022 () | |
| In 2023 () | |

*Display This Question:*

*If Since 2019, was driving for a taxi or FHV company or companies your only job, or did you do other... = Had other work too*

add_work Did you do any additional work in 2019 or 2020 for which you received or expect to receive a "W-2" wage and tax statement?

- Yes, Received W-2 for work that was performed in 2019 (1)
- Yes, Received W-2 for work that was performed in 2020 (4)
- Yes, Received W-2 for work that was performed in both 2019 and 2020 (5)
- No (2)
- Don't Know/Unsure (3)

*Display This Question:*

*If Did you do any additional work in 2019 or 2020 for which you received or expect to receive a "W-2... = Yes, Received W-2 for work that was performed in 2019*

*Or Did you do any additional work in 2019 or 2020 for which you received or expect to receive a "W-2... = Yes, Received W-2 for work that was performed in 2020*

*Or Did you do any additional work in 2019 or 2020 for which you received or expect to receive a "W-2... = Yes, Received W-2 for work that was performed in both 2019 and 2020*

add_work_con Were you still employed in this W-2 job before the COVID crisis?

- ○ Yes (1)
- ○ No (2)

**End of Block: Number of jobs to gauge eligibility**

**Start of Block: Interactions with the UI system**

PUA Have you applied for unemployment benefits since March 2020? This question is only asking about application for unemployment benefits including Pandemic Unemployment Assistance (PUA), not whether you have begun to receive any unemployment benefits as of this time.

- ○ Yes (1)
- ○ No (2)

*Display This Question:*

*If Have you applied for unemployment benefits since March 2020? This question is only asking about... = No*

no_ui_reason You indicated you DID NOT apply for unemployment benefits since March 2020, could you briefly tell us why? Select ALL that apply

- [ ] Not needed (5)
- [ ] Don't believe I'm eligible (1)
- [ ] Not sure how to apply (2)
- [ ] Too complicated to apply (3)
- [ ] Other (Please indicate reason in the text box) (4) _____

*Display This Question:*

*If Have you applied for unemployment benefits since March 2020? This question is only asking about... = Yes*

JS

ui_app_monthyear You indicated that you applied for unemployment insurance benefits since March 2020? Approximately when did you first apply for benefits?

- ○ Month and Year of unemployment application (1) _____

*Display This Question:*

*If Have you applied for unemployment benefits since March 2020? This question is only asking about... = Yes*

ui_state You indicated that you applied for unemployment insurance benefits since March 2021. What state did you apply for benefits in?

- New York (1)
- New Jersey (2)
- Connecticut (3)
- Other (Please indicate state in text box) (4) _____

*Display This Question:*

*If Have you applied for unemployment benefits since March 2020? This question is only asking about... = Yes*

ui_type Did you apply for regular Unemployment Insurance (UI), or the Pandemic Unemployment Assistance (PUA) as part of the CARES Act? (Note: Both regular UI and PUA recipients were eligible to receive the additional $600 benefit that ran through July 2020.)

- Regular Unemployment Insurance (1)
- New Pandemic Unemployment Assistance (2)
- Don't Know/Unsure (3)

*Display This Question:*

*If Have you applied for unemployment benefits since March 2020? This question is only asking about... = Yes*

ui_proof Which of the following did you supply as proof of income? Select ALL that apply.

- [ ] W2 Tax Form (6)
- [ ] 1099 Tax Form (1)
- [ ] Schedule C/SE Tax Filing (2)
- [ ] Quarterly Tax Filings (3)
- [ ] Statement or Receipts supplied by FHV or taxi company (4)
- [ ] Other (Please indicate in text box) (5) _____

*Display This Question:*

*If Have you applied for unemployment benefits since March 2020? This question is only asking about... = Yes*

ui_receive You indicated that you applied for unemployment benefits since March 2020. Did you begin to receive these benefits?

- ○ Yes (1)
- ○ No, claim is still pending (2)
- ○ No, claim was denied (3)

*Display This Question:*

*If You indicated that you applied for unemployment benefits since March 2020. Did you begin to recei... = Yes*

ui_months You indicated that you have begun to receive unemployment benefits. In what months did you receive these payments? (Select ALL that apply)

- [ ] March 2020 (1)
- [ ] April 2020 (2)
- [ ] May 2020 (3)
- [ ] June 2020 (4)
- [ ] July 2020 (5)
- [ ] August 2020 (6)
- [ ] September 2020 (7)
- [ ] October 2020 (8)
- [ ] November 2020 (9)
- [ ] December 2020 (10)
- [ ] January 2021 (11)
- [ ] February 2021 (13)
- [ ] March 2021 (14)
- [ ] April 2021 (15)
- [ ] May 2021 (16)
- [ ] June 2021 (17)

- [ ] July 2021 (18)
- [ ] August 2021 (19)
- [ ] September 2021 (20)
- [ ] October 2021 (21)
- [ ] November 2021 (22)
- [ ] December 2021 (23)

**End of Block: Interactions with the UI system**

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**Start of Block: Expenses**

Expenses Intro The next series of questions ask about your typical weekly operating expenses and how they may have changed since the COVID crisis.

---

exp_19 We are trying to understand how your expenses have changed SINCE the pandemic started. Please use the slider to select an approximate dollar value. If weekly costs were greater than $1,000, please select $1,000. If you did not have any expenses, select "Not Applicable." **Thinking back to 2019.** Please recall your weekly expenses for each of the following categories:

| | Total weekly expenses ($) | Not Applicable |
|---|---|---|
| | 0 100 200 300 400 500 600 700 800 900 1000 | |

| | |
|---|---|
| Gasoline () |  |
| Lease Costs () |  |
| Other direct operating expenses (vehicle cleaning fees, etc) () |  |
| Other miscellaneous expenses (water bottles, etc) () |  |

Page Break

exp_20 Please use the slider to select an approximate dollar value. If weekly costs were greater than $1,000, please select $1,000. If you did not have any expenses, select "Not Applicable."
**Now please recall 2020:**

| | Total weekly expenses ($)<br>0 100 200 300 400 500 600 700 800 900 1000 | Not Applicable |
|---|---|---|
| Gasoline () |  | |
| Lease Costs () |  | |
| Other direct operating expenses (cleaning fees, etc) () |  | |
| Other Miscellaneous Expenses (water bottles, etc) () |  | |

Page Break

exp_21 Please use the slider to select an approximate dollar value. If weekly costs were greater than $1,000, please select $1,000. If you did not have any expenses, select "Not Applicable."
**Now please recall 2021:**

| | Total weekly expenses ($)<br>0 100 200 300 400 500 600 700 800 900 1000 | Not Applicable |
|---|---|---|
| Gasoline () |  | |
| Lease Costs () |  | |
| Other direct operating expenses (vehicle cleaning fees, etc) () |  | |
| Other miscellaneous expenses (water bottles, etc) () |  | |

Page Break

exp_22 Please use the slider to select an approximate dollar value. If weekly costs were greater than $1,000, please select $1,000. If you did not have any expenses, select "Not Applicable."
**Now please recall 2022:**

| | Total weekly expenses ($)<br>0 100 200 300 400 500 600 700 800 900 1000 | Not Applicable |
|---|---|---|
| Gasoline () |  | |
| Lease Costs () |  | |
| Other direct operating expenses (vehicle cleaning fees, etc) () |  | |
| Other miscellaneous expenses (water bottles, etc) () |  | |

Page Break

exp_23 Please use the slider to select an approximate dollar value. If weekly costs were greater than $1,000, please select $1,000. If you did not have any expenses, select "Not Applicable."
**Now please recall 2023:**

| | Total weekly expenses ($)<br>0 100 200 300 400 500 600 700 800 900 1000 | Not Applicable |
|---|---|---|
| Gasoline () |  | |
| Lease Costs () |  | |
| Other direct operating expenses (vehicle cleaning fees, etc) () |  | |
| Other miscellaneous expenses (water bottles, etc) () |  | |

Page Break

*Display This Question:*

*If Please use the slider to select an approximate dollar value. If weekly costs were greater than $1... [ Lease Costs ] > 0*

*Or Please use the slider to select an approximate dollar value. If weekly costs were greater than $1... [ Lease Costs ] > 0*

*Or Please use the slider to select an approximate dollar value. If weekly costs were greater than $1... [ Lease Costs ] > 0*

*Or We are trying to understand how your expenses have changed SINCE the pandemic started. Please use... [ Lease Costs ] > 0*



lease_defer Were you able to forgo or defer payment on your lease after March 2020 due to Covid?

- [ ] (1) I was able to forgo or defer payment on my lease after March 2020 due to Covid
- [ ] I was not able to forgo or defer payment on my lease at any time. (2)

Page Break

*Display This Question:*

*If Please use the slider to select an approximate dollar value. If weekly costs were greater than $1... [ Lease Costs ] > 0*

*Or We are trying to understand how your expenses have changed SINCE the pandemic started. Please use... [ Lease Costs ] > 0*

*Or Please use the slider to select an approximate dollar value. If weekly costs were greater than $1... [ Lease Costs ] > 0*

*Or Please use the slider to select an approximate dollar value. If weekly costs were greater than $1... [ Lease Costs ] > 0*

forgo_qrtyear Which quarters were you able to forgo or defer payment on your lease due to Covid?

| | 2020 (1) | 2021 (2) | 2022 (3) | 2023 (4) |
|---|---|---|---|---|
| First Quarter (Jan-Mar) (2) | ☐ | ☐ | ☐ | ☐ |
| Second Quarter (Apr-Jun) (3) | ☐ | ☐ | ☐ | ☐ |
| Third Quarter (Jul-Sept) 2019 (4) | ☐ | ☐ | ☐ | ☐ |
| Fourth Quarter (Oct-Dec) (5) | ☐ | ☐ | ☐ | ☐ |

*Display This Question:*

*If Were you able to forgo or defer payment on your lease after March 2020 due to Covid? = I was able to forgo or defer payment on my lease after March 2020 due to Covid*

lease_terms Please tell us about the terms of your lease that allowed you to forgo or defer payment.

_____

Page Break

add_precautions In addition to the expenses listed in the previous question, has the pandemic forced you to pay for any additional precautions when driving (e.g., installing protective barriers, purchasing hand sanitizer, disinfectant products, and/or Personal Protective Equipment (PPE))? This does not include any materials provided to you by the taxi or For-Hire-Vehicle (FHV) company or companies.

- ○ Yes, I am taking additional precautions. If yes, please provide an estimate of your total expenses below: (1) _____
- ○ No, I am not taking any additional precautions (2)

*Display This Question:*

*If In addition to the expenses listed in the previous question, has the pandemic forced you to pay f... = Yes, I am taking additional precautions. If yes, please provide an estimate of your total expenses below:*

prec_buy What did you purchase as an additional precaution against Covid when driving beyond what was provided by the taxi or For-Hire-Vehicle (FHV) company or companies?

_____

**End of Block: Expenses**

**Start of Block: Other effects and coping strategies**

behav_delta Has the pandemic changed your driving behavior in any way over the course of pandemic? For example, are you avoiding certain neighborhoods or areas, refusing riders, or only working during certain hours?

| | 2020 (1) | 2021 (2) | 2022 (3) | 2023 (4) |
|---|---|---|---|---|
| No change in behavior (5) | ☐ | ☐ | ☐ | ☐ |
| Avoiding certain neighborhoods or areas (1) | ☐ | ☐ | ☐ | ☐ |
| Refusing riders (2) | ☐ | ☐ | ☐ | ☐ |
| Only working during certain hours (3) | ☐ | ☐ | ☐ | ☐ |
| Other (please indicate in text box below): (4) | ☐ | ☐ | ☐ | ☐ |

Page Break

depend Were you the primary caregiver for a child or other dependent (such as an elderly parent) in 2020? Select all that apply.

- [ ] Yes, at least one child under 6. (1)
- [ ] Yes, at least one child between ages 6 and 18. (2)
- [ ] Yes, other dependent, such as an elderly parent (3)

Page Break

bene_other Have you accessed any of these other benefits/services since 2020? Please select all that apply.

- [ ] Food stamps (1)
- [ ] Food pantries (2)
- [ ] Shelters (3)
- [ ] Eviction relief / rental assistance (6)
- [ ] Paycheck Protection Program (PPP) (4)
- [ ] None of the above (5)

Page Break

other_work Have you done any of the following since January 2020? Select all that apply

- [ ] Delivery work for other companies like Instacart, Uber Eats, Amazon, providing groceries, takeout or package delivery services (1)
- [ ] Delivery work provided by the Taxi and Limousine Commission (TLC) (2)
- [ ] Took another job outside of the gig economy (3)
- [ ] Other (please indicate in the text box below): (6)

_____

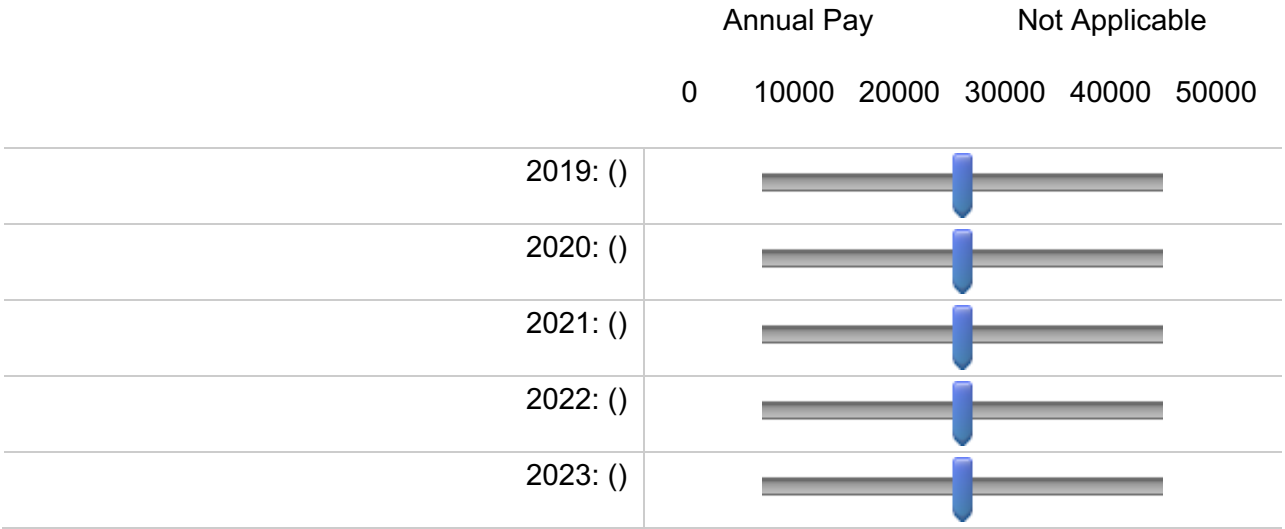
Page Break

*Display This Question:*

*If Have you done any of the following since January 2020? Select all that apply = Delivery work for other companies like Instacart, Uber Eats, Amazon, providing groceries, takeout or package delivery services*

delivery_pay You indicated that you did delivery work for other companies like Instacart, Uber Eats, Amazon, providing groceries, takeout or package delivery services.

The following questions ask about your annual pay incluing for **for delivery work only**? If you did not do delivery work in that year please select "Not Applicable."




Page Break

Page Break

*Display This Question:*

*If Have you done any of the following since January 2020? Select all that apply = Other (please indicate in the text box below):*

delivery_hours You indicated that you did delivery work for other companies like Instacart, Uber Eats, Amazon, providing groceries, takeout or package delivery services. The following questions ask about your HOURS worked as a delivery driver PER WEEK (hours include time spent on delivery or waiting for a delivery order). Please think about a TYPICAL WEEK in the last month you did delivery work. Did you drive more hours, fewer hours or about the same number of hours as your previous driving work?"

| | Worked more hours. (2) | Worked about the same number of hours. (3) | Worked fewer hours. (4) | Did not do delivery for another service this year. (5) |
|---|---|---|---|---|
| 2020 (1) | ○ | ○ | ○ | ○ |
| 2021 (2) | ○ | ○ | ○ | ○ |
| 2022 (3) | ○ | ○ | ○ | ○ |
| 2023 (4) | ○ | ○ | ○ | ○ |

*Display This Question:*

*If Have you done any of the following since January 2020? Select all that apply = Other (please indicate in the text box below):*

delivery_pay You indicated that you did delivery work for other companies like Instacart, Uber Eats, Amazon, providing groceries, takeout or package delivery services. The following questions ask about your WEEKLY PAY from delivery work ONLY. Please think about a TYPICAL WEEK in the last month you did delivery work. Did you earn more, less or about the same as your previous driving work?

| | I earned more. (2) | I earned about the same. (3) | I earned less. (4) | I did not do delivery for another service this year. (5) |
|---|---|---|---|---|
| 2020 (1) | ○ | ○ | ○ | ○ |
| 2021 (2) | ○ | ○ | ○ | ○ |
| 2022 (3) | ○ | ○ | ○ | ○ |
| 2023 (4) | ○ | ○ | ○ | ○ |

**End of Block: Other effects and coping strategies**

**Start of Block: Safety and health concerns**

*Display This Question:*

*If Have you done any of the following since January 2020? Select all that apply = Other (please indicate in the text box below):*

*Or Or Have you done any of the following since January 2020? Select all that apply Text Response Is Not Empty*

hi_cover Do you have health insurance? Please indicate your health insurance coverage for each year.

| | 2019 (1) | 2020 (2) | 2021 (3) | 2022 (4) | 2023 (5) |
|---|---|---|---|---|---|
| No access to heath insurance (1) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Yes, through employer provided health insurance from another job (2) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Yes, through a spouse, partner or parent (3) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Yes, through a Health Insurance Marketplace (sometimes called Obamacare) (4) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Yes, through Medicaid (5) | ☐ | ☐ | ☐ | ☐ | ☐ |
| Other (please indicate in the text box below): (6) | ☐ | ☐ | ☐ | ☐ | ☐ |

Page Break

risk_self In your view, have you considered **yourself** part of a group at risk of serious complications from COVID? How has this changed year to year? Please indicate below your appropriate level of risk per year.

| | Low-Risk (1) | Moderate-to-Medium Risk (2) | High-Risk (3) |
|---|---|---|---|
| 2020 (1) | ○ | ○ | ○ |
| 2021 (2) | ○ | ○ | ○ |
| 2022 (3) | ○ | ○ | ○ |
| 2023 (4) | ○ | ○ | ○ |

Page Break

risk_livewith In your view, is **anyone you live with** part of a group at risk of serious complications from COVID? How has this changed year to year? Please indicate below the appropriate level of risk for your household members per year.

| | Low-Risk (1) | Moderate-to-Medium Risk (2) | High-Risk (3) |
|---|---|---|---|
| 2020 (1) | ○ | ○ | ○ |
| 2021 (2) | ○ | ○ | ○ |
| 2022 (3) | ○ | ○ | ○ |
| 2023 (4) | ○ | ○ | ○ |

Page Break

vax_year When was your last COVID-19 immunisation or booster? If you do not intend to get vaccinated, please indicate your reason why.

- ○ 2021 (5)
- ○ 2022 (1)
- ○ 2023 (2)
- ○ 2024 (6)
- ○ No, I am not vaccinated yet. Optional: please indicate a reason. (7) _____

End of Block: Safety and health concerns

Start of Block: Demographics

gender How do you identify?

- ○ Male (1)
- ○ Female (2)
- ○ Other (3)

age How old are you?

- ○ 18-24 (1)
- ○ 25-34 (2)
- ○ 35-44 (3)
- ○ 45-54 (4)
- ○ 55-64 (5)
- ○ 65+ (6)

hispanic Are you of Hispanic, Latino or Spanish origin?

- ○ Yes (1)
- ○ No (2)

race What is your race?

- ○ White (1)
- ○ Black or African-American (2)
- ○ American Indian or Alaska Native (3)
- ○ Asian or Asian-American (4)
- ○ Native Hawaiian or Pacific Islander (5)
- ○ Other race (please specify) (6) _____
- ○ Multiple races (please specify) (7) _____

lang What is your first or native language?

- ○ English (1)
- ○ Spanish (2)
- ○ Bengali (3)
- ○ Russian (4)
- ○ Arabic (5)
- ○ Other (please specify) (6) _____

Page Break

covid_other Is there anything else you would like to mention about your experience as a taxi or For-Hire-Vehicle (FHV) driver **during COVID-19?**

_____

other Are there any **other challenges** you would like to share about your experiences as a taxi of For-Hire-Vehicle (FHV) driver?

_____

End of Block: Demographics

Start of Block: Email Address Request



incentive_email To receive your $20 Amazon gift card for completing this survey, please enter an email address below. This email address will ONLY be used for delivery. You should receive your gift card within 24 hours.

_____

End of Block: Email Address Request